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Climate Change, Mortality and Adaptation: Evidence from Annual Fluctuations in Weather in the U.S.

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ABSTRACT

This paper produces the first large-scale estimates of the US health related welfare costs due to climate change. The full welfare impact will be reflected in health outcomes and increased consumption of goods that preserve individuals' health. Using the presumably random year-to-year variation in temperature and two state of the art climate models, the analysis suggests that under a 'business as usual' scenario climate change will lead to an increase in the overall US annual mortality rate of approximately 2% at the end of the 21st century. Among different age groups, the estimated mortality increases are largest for infants. Individuals are likely to respond to higher temperatures by increasing air conditioning usage; the analysis suggests that climate change will lead to increases in annual residential energy consumption of up to 32% by the end of the century. Overall, the estimates suggest that the present discounted value of willingness to pay to avoid the climate change induced mortality and energy impacts predicted to occur over the remainder of the 21st century is about $900 billion (2006$) or 6.8% of 2006 GDP. This estimate of willingness to pay is statistically insignificant and is likely to overstate the long-run costs of climate change on these outcomes, because climate change will unfold gradually and individuals can engage in a wider set of adaptations that will mitigate costs in the longer run.

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Introduction

The climate is a key ingredient in the earth's complex system that sustains human life and wellbeing. There is a growing consensus that emissions of greenhouse gases due to human activity will alter the earth's climate, most notably by causing temperatures, precipitation levels, and weather variability to increase. According to the UN's Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report, climate change is likely to affect human health directly through changes in temperature and precipitation and indirectly through changes in the ranges of disease vectors (e.g., mosquitoes) and other channels (IPCC Working Group II, 2007). The design of optimal climate change mitigation policies requires credible estimates of the health and other benefits of reductions in greenhouse gases; current evidence on the magnitudes of the direct and indirect impacts, however, is considered insufficient for reliable conclusions (WHO 2003).[1]

Conceptual and statistical problems have undermined previous efforts to develop estimates of the health related welfare costs of climate change. The conceptual problem is that the canonical Becker-Grossman economic models of health production predict that individuals will respond to climate changes that threaten their health by purchasing goods that mitigate the health damages (Grossman 2000). In the extreme, it is possible that individuals would fully "self-protect" such that climate change would not affect measured health outcomes. In this case, an analysis that solely focuses on health outcomes would incorrectly conclude that climate change has zero impact on welfare.

On the statistical side, there are at least three challenges. First, there is a complicated, dynamic relationship between temperature and mortality, which can cause the short-run relationship between temperature and mortality to differ substantially from the long-run (Huynen et al. 2001; Deschênes and Moretti 2007).[2] Second, individuals' locational choices---which determine exposure to a climate---are related to health and socioeconomic status, so this form of selection makes it difficult to uncover the

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[1] See Tol (2002a and 2002b) for overall estimates of the costs of climate change, which are obtained by summing costs over multiple areas including human health, agriculture, forestry, species/ecosystems, and sea level rise. Deschênes and Greenstone (2007) provide evidence on the impacts on the US agricultures sector. Also, see Schlenker, Hanemann, and Fisher (2006).

[2] For example, Deschênes and Moretti (2007) document the importance of forward displacement or "harvesting" on hot days.

causal relationship between temperature and mortality. Third, the relationship between temperature and health is highly nonlinear and likely to vary across age groups.

This paper develops measures of the welfare loss associated with the direct risks to health posed by climate change in the US that confront these conceptual and statistical challenges. Specifically, the paper reports on statistical models for age group-by-county mortality rates and for state-level residential energy consumption (perhaps the primary form of protection against high temperatures via air conditioning) that model temperature semi-parametrically. The mortality models include county and state-by-year fixed effects, while the energy ones include state and Census division-by-year fixed effects. Consequently, the temperature variables are identified from the unpredictable and presumably random year-to-year local variation in temperature, so concerns about omitted variables bias are unlikely to be important. Both the mortality and energy consumption results reveal U-shaped relationships where the costs are highest at very high and low temperatures.

We combine the estimated impacts of temperature on mortality and energy consumption with predicted changes in climate from 'business as usual' scenarios to develop estimates of the health related welfare costs of climate change in the US. The preferred mortality estimates suggest an increase in the overall annual mortality rate of approximately 2% by the end of the century. Among different age groups, the estimated mortality increases are largest for infants. The energy results suggest that by the end of the century climate change will cause annual US residential energy consumption to increase by up to 32%. Overall, the estimates suggest that the present discounted value of willingness to pay to avoid the climate change induced mortality and energy impacts predicted to occur over the remainder of the 21st century is about $900 billion (2006$) or 6.8% of 2006 GDP. Notably, the null that the measure of willingness to pay is zero cannot be rejected at conventional significance levels.

There are a few important caveats to these calculations and, more generally, to the analysis. The estimated impacts likely overstate the mortality and adaptation costs, because the analysis relies on inter-annual variation in weather, and less expensive adaptations (e.g., migration) will be available in response to permanent climate change. On the other hand, the estimated welfare losses fail to include the impacts on other health-related determinants of welfare (e.g., morbidities and quality of life) that may be affected

by climate change, so in this sense they are an underestimate. Additionally, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that the climate change predictions are correct, relative prices (e.g., for energy and medical services) will remain constant, the same energy and medical technologies will prevail, and the demographics of the US population (e.g., age structure) and their geographic distribution will remain unchanged. These are strong assumptions, but their benefit is that they allow for a transparent analysis based on data rather than on unverifiable assumptions.

The analysis is conducted with the most detailed and comprehensive data available on mortality, energy consumption, weather, and climate change predictions for fine US geographic units. The mortality data come from more than 73.2 million death certificates in the 1968-2002 Compressed Mortality Files, the energy data are from the Energy Information Administration, and the weather data are from the thousands of weather stations located throughout the US. We utilize two sets of end-of-century (i.e., 2070-2099) daily climate change predictions that represent "business-as-usual" scenarios.

Finally, the paper's approach mitigates or solves the conceptual and statistical problems that have plagued previous research (e.g., Bosello et al. 2006, Dessai 2003, Hayhoe et al. 2004). First, the availability of data on energy consumption means that we can measure the impact on mortality and self-protection expenditures. Second, the estimation of annual mortality equations, rather than daily ones, mitigates concerns about failing to capture the full mortality impacts of temperature shocks. Third, the county fixed effects adjust for any differences in unobserved health across locations due to sorting. Fourth, we model daily temperature semi-parametrically by using ten separate variables, so we do not rely on functional form assumptions to infer the impacts of the hottest and coldest days. Fifth, we estimate separate mortality models for four age groups, which allows for substantial heterogeneity in the impacts of temperature.

The paper proceeds as follows. Section I briefly reviews the patho-physiological and statistical evidence on the relationship between weather and mortality. Section II provides the conceptual framework for our approach. Section III describes the data sources and reports summary statistics. Section IV presents the econometric approach, and Section V describes the results. Section VI assesses

the magnitude of our estimates of the effect of climate change and discusses a number of important caveats to the analysis. Section VII concludes the paper.

I. Background on the Relationship between Weather and Mortality

Individuals' heat regulation systems enable them to cope with high and low temperatures. Specifically, high and low temperatures generally trigger an increase in the heart rate in order to increase blood flow from the body to the skin, leading to the common thermoregulatory responses of sweating in hot temperatures and shivering in cold temperatures. These responses allow individuals to pursue physical and mental activities without endangering their health within certain ranges of temperature. Temperatures outside of these ranges pose dangers to human health and can result in premature mortality. This section provides a brief review of the mechanisms and the challenges for estimation.

Hot Days. An extensive literature documents a relationship between extreme temperatures (usually during heatwaves) and mortality (e.g., Klineberg 2002; Huynen et al. 2001; Rooney et al. 1998). These excess deaths are generally concentrated among causes related to cardiovascular, respiratory, and cerebrovascular diseases. The need for body temperature regulation imposes additional stress on the cardiovascular and respiratory systems. In terms of specific indicators of body operations, elevated temperatures are associated with increases in blood viscosity and blood cholesterol levels. It is not surprising that previous research has shown that access to air conditioning greatly reduces mortality on hot days (Semenza et al. 1996).

An important feature of the relationship between heat and mortality is that the number of deaths immediately caused by a period of very high temperatures is at least partially compensated for by a reduction in the number of deaths in the period immediately subsequent to the hot day or days (Basu and Samet 2002; Deschênes and Moretti 2007). This pattern is called forward displacement or "harvesting," and it appears to occur because heat affects individuals who were already very sick and would have died in the near term. Since underlying health varies with age, these near-term displacements are more prevalent among the elderly.

Cold Days. Cold days are also a risk factor for mortality. Exposure to very cold temperatures

causes cardiovascular stress due to changes in blood pressure, vasoconstriction, and an increase in blood viscosity (which can lead to clots), as well as levels of red blood cell counts, plasma cholesterol, and plasma fibrinogen (Huynen et al. 2001). Further, susceptibility to pulmonary infections may increase because breathing cold air can lead to bronchoconstriction.

Deschênes and Moretti (2007) provide the most comprehensive evidence on the impacts of cold days on mortality. They find "evidence of a large and statistically significant effect on mortality within a month of the cold wave. This effect appears to be larger than the immediate effect, possibly because it takes time for health conditions associated with extreme cold to manifest themselves and to spread" (Deschênes and Moretti 2007). Thus, in the case of cold weather, it may be that there are delayed impacts and that the full effect of a cold day takes a few weeks to manifest itself. Further, they find that the impact is most pronounced among the young and elderly and concentrated among cardiovascular and respiratory diseases.

Implications. The challenge for this study, and for any study focused on substantive changes in life expectancy, is to develop estimates of the impact of temperature on mortality that are based on the full long-run impact on life expectancy. In the case of hot days, the previous literature suggests that this task requires purging the temperature effects of the influence of harvesting or forward displacement. In the case of cold days, the mortality impact may accumulate over time. In both cases, the key point is that the full impact of a given day's temperature may take numerous days to manifest fully.

Our review of the literature suggests that the full mortality impacts of cold and hot days are evident within 30 days (Huynen et al. 2001; Deschênes and Moretti 2007). The below econometrics section outlines a method that allows the mortality impacts of temperature to manifest themselves over long periods of time. Further, the immediate and longer run effects of hot and cold days are likely to vary across the populations, with larger impacts among relatively unhealthy subpopulations. One important determinant of healthiness is age, with the old and young being particularly sensitive to environmental insults. Consequently, we conduct separate analyses for four separate age categories.

II. Conceptual Framework

In principle, it is possible to capture the full welfare effects of climate change through observations on the land market. Since land is a fixed factor, it will capture all the differences in rents associated with differences in climate (Rosen 1974).[3] The advantage of this approach is that in principle the full impact of climate change can be summarized in a single market. Despite the theoretical and practical appeal of this approach, it is unlikely to provide reliable estimates of the welfare impacts of climate change. We base this conclusion on a series of recent papers which suggest that the results from the estimation of cross-sectional hedonic equations for land prices are quite sensitive to seemingly minor decisions about the appropriate control variables, sample, and weighting and generally appear prone to misspecification (Black 1999; Chay and Greenstone 2005; Deschênes and Greenstone 2007; Greenstone and Gallagher 2008). An alternative approach is to develop estimates of the impact of climate change in a series of key sectors, which could then be summed. This paper proceeds in this spirit.

Our goal is to develop a partial estimate of the health-related welfare impact of climate change in the US. This section begins by reviewing a Becker-Grossman style 1-period model of health production (Grossman 2000). It then uses the results to derive a practical expression for the health-related welfare impacts of climate change (Harrington and Portney 1987). This expression guides the subsequent empirical analysis. The section then discusses the implications of our estimation strategy which relies on inter-annual fluctuations in weather for the interpretation of the resulting welfare measures.

A Practical Expression for Willingness to Pay/Accept (WTP/WTA) for an Increase in Temperature. We assume a representative individual consumes a jointly aggregated consumption good, x_C. Their other consumption good is their mortality risk, which leads to a utility function of:

(1) $U = U[x_C, s]$,

where s is the survival rate. The production function for survival is expressed as:

(2) $s = s(x_H, T)$,

so that survival is a function of x_H, which is a private good that increases the probability of survival, and ambient temperature, T. Energy consumption is an example of x_H, since energy is used to run air conditioners, which affect survival on hot days. We define x_H such that $\partial s/\partial x_H > 0$. For expositional

[3] It is also possible that climate differences are reflected in the labor market Roback (1982) model.

purposes, we assume that climate change leads to an increase in temperatures in the summer only when higher temperatures are harmful for health so $\partial s/\partial T < 0$.

The individual faces a budget constraint of the form:

(3) $I - x_C - px_H = 0$,

where I is exogenous earnings or income and prices of x_C and x_H are 1 and p, respectively.

The individual's problem is to maximize (1) through her choices of x_C and x_H, subject to (2) and (3). In equilibrium, the ratio of the marginal utilities of consumption of the two must be equal to the ratio of the prices: $[(\partial U/\partial s)\cdot(\partial s/\partial x_H)]/[\partial U/\partial x_C] = p$. Solution of the maximization problem reveals that the input demand equations for x_C and x_H are functions of prices, income, and temperature. Further, it reveals the indirect utility function, V, which is the maximum utility obtainable given p, I, and T.

We utilize V(p, I, T) to derive an expression for the welfare impact of climate change, holding constant utility (and prices). Specifically, we consider changes in T as climate change is predicted to increase temperatures. In this case, it is evident that the consumer must be compensated for changes in T with changes in I when utility is held constant. The point is that in this setting income is a function of T, which we denote as I*(T). Consequently, for a given level of utility and fixed p, there is an associated V(I*(T),T).

Now, consider the total derivative of V with respect to T along an indifference curve:

$dV/dT = V_I \cdot (dI^*(T)/dT) + \partial V/\partial T = 0$ or $dI^*(T)/dT = -(\partial V/\partial T)/(\partial V/\partial I)$.

The term dI*(T)/dT is the change in income necessary to hold utility constant for a change in T. In other words, it measures willingness to pay (accept) for a decrease (increase) in summer temperatures. Thus, it is the theoretically correct measure of the health-related welfare impact of climate change.

Since the indirect utility function is not observable, it is useful to express dI*(T)/dT in terms that can be measured with available data sets. By using the derivatives of V and the first order conditions from the above maximization problem, it can be rewritten as $dI^*(T)/dT = -p\ [(\partial s/\partial T)/(\partial s/\partial x_H)]$. In principle, it is possible to measure these partial derivatives, but it is likely infeasible since data files containing measures of the complete set of x_H are unavailable generally. Put another way, data limitations prevent the estimation of the production function specified in equation (2). However, a few

algebraic manipulations, based on the first order conditions and that $\partial s/\partial T$ = ds/dT – $(\partial s/\partial x_H)(\partial x_H/\partial T)$ (because ds/dT= $(\partial s/\partial x_H)(\partial x_H/\partial T) + \partial s/\partial T$), yields:

(4) $dI^*(T)/dT = - ds/dT\ (\partial U/\partial s)/\lambda + p\ \partial x_H/\partial T$,

where λ is the Lagrangian multiplier from the maximization problem or the marginal utility of income.

As equation (4) makes apparent, willingness to pay/accept for a change in temperature can be inferred from changes in s and x_H. Since temperature increases raise the effective price of survival, theory would predict that $ds/dT \leq 0$ and $\partial x_H/\partial T \geq 0$. Depending on the exogenous factors, it is possible that there will be a large change in the consumption of x_H (at the expense of consumption of x_C) and little change in s. The key point for this paper's purpose is that the full welfare effect of the exogenous change in temperature is reflected in changes in the survival rate <u>and</u> the consumption of x_H.

It is of tremendous practical value that all of the components of equation (4) can be measured. The total derivative of the survival function with respect to temperature (ds/dT), or the dose-response function, is obtained through the estimation of epidemiological-style equations that do not control for x_H. We estimate such an equation below.[4] The term $(\partial U/\partial s)/\lambda$ is the dollar value of the disutility of a change in the survival rate. This is known as the value of a statistical life (Thaler and Rosen 1976) and empirical estimates are available (e.g., Ashenfelter and Greenstone 2004). The last term is the partial derivative of x_H with respect to temperature multiplied by the price of x_H. We estimate how energy consumption changes with temperature (i.e., $\partial x_H/\partial T$) below, and information on energy prices is readily available.

It is appealing that the paper's empirical strategy can be directly connected to an expression for WTP/WTA, but this connection has some limitations worth highlighting from the outset. The empirical estimates will only be a partial measure of the health-related welfare loss, because climate change may affect other health outcomes (e.g., morbidity rates). Further, although energy consumption likely captures a substantial component of health preserving or defensive expenditures, climate change may induce other forms of adaptation (e.g., substituting indoor exercise for outdoor exercise or changing the time of day

[4] Previous research on the health impacts of air pollution almost exclusively estimate these dose-response functions, rather than the production functions specified in equation (2) (e.g., Chay and Greenstone 2003a and 2003b).

when one is outside).[5] These other outcomes are unobservable in our data files, so the resulting welfare estimates will be incomplete and understate the costs of climate change.

Adaptation in the Short and Long Runs. The one-period model sketched in the previous subsection obscures an issue that may be especially relevant in light of our empirical strategy which relies on inter-annual fluctuations in weather to learn about the welfare consequences of permanent climate change. It is easy to turn the thermostat down and use more air conditioning on hot days, and it is even possible to purchase an air conditioner in response to a single year's heat wave. A number of adaptations, however, cannot be undertaken in response to a single year's weather realization. For example, permanent climate change is likely to lead individuals to make their homes more energy efficient or perhaps even to migrate (presumably to the North). Our approach fails to capture these adaptations.

Figure 1 illustrates this issue in the context of alternative technologies to achieve a given indoor temperature. Household annual energy related expenditures are on the y-axis and the annual ambient temperature, summarized by a single number T, is on the x-axis. The figure depicts the cost functions associated with three different technologies. These cost functions all have the form $C_j = rF_j + f_j(T)$, where C is annual energy related expenditures, F is the capital cost of the technology, r is the user cost of capital, and f(T) is the marginal cost that is a function of temperature, T. The j subscripts index the technology.[6] As the figure demonstrates, the cost functions differ in their fixed costs, which determine where they intersect the y-axis, and their marginal cost functions or how costs rise with temperature.

The cost minimizing technology varies with expectations about temperature. For example, Technology 1 minimizes costs between T_1 and T_2 and the costs associated with Technologies 1 and 2 are identical at T_2 where the cost functions cross (i.e., point B), and Technology 2 is optimal at temperatures between T_2 and T_4. The outer envelope of least cost technology choices is depicted as the broken line and

[5] Energy consumption may affect utility through other channels in addition to its role in self-protection. For example, high temperatures are uncomfortable. It would be straightforward to add comfort to the utility function and make comfort a function of temperature and energy consumption. In this case, this paper's empirical exercise would fail to capture the impact of temperature on heat but the observed change in energy consumption would reflect its role in self-protection and comfort.

[6] For illustrative purposes, consider the technologies to be central air conditioning without the use of insulation in the construction of the house (Technology 1), central air conditioning with insulation (Technology 2), and zonal air conditioning with insulation (Technology 3).

this is where households will choose to locate.[7] Notably, there are no theoretical restrictions on the outer envelope as it is determined by technologies, so it could be convex, linear, or concave.

The available data sets provide information on annual energy consumption quantities but not on annual energy expenditures. This means that existing data sources can only identify the part of the cost function associated with the marginal costs of ambient temperatures or f(T). Further, it highlights that the estimation of the outer envelope with data on quantities can reveal the equilibrium relationship between energy consumption and temperature. However, it is not informative about how total energy related expenditures vary with temperature, precisely because the fixed costs associated with different technologies are unobserved. One clear implication is that it is infeasible to determine the impact of climate change on total energy expenditures with cross-sectional data as is claimed by Mansur, Mendelsohn, and Morrison (2007).

We now discuss what can be learned from inter-annual variation in temperature and a panel data file on residential energy consumption quantities. Consider an unexpected increase in temperatures from T_1 to T_3 for a single year, assuming that it is infeasible for households to switch technologies in response. The representative household's annual energy related expenditures would increase from A to C' and with fixed prices this is entirely captured by the increase in energy consumption quantities. If the change in temperature were permanent, as would be the case with climate change, then the household would switch to Technology 2 and their annual energy related expenditures would increase from A to C (again this cannot be inferred from data on energy consumption quantities alone). Thus, the change in energy related costs in response to a single year's temperature realization overstates the increase in energy costs, relative to the change associated with a permanent temperature increase. It is noteworthy that the changes in costs associated with a new temperature $\geq T_1$ and $\leq T_2$ are equal regardless of whether it is transitory or permanent, because the outer envelope and Technology 1 cost curve are identical over this range.

To summarize, this section has derived an expression for WTP/WTA for climate change that can be estimated with available data sets. The first subsection pointed out that due to data limitations we can

[7] For simplicity, we assume that there is no variation in temperature across years at a location, and households base their technology choice on this information. In reality, technology choice depends on the full probability distribution function of ambient temperatures at a location.

only examine a subset of the outcomes likely to be affected by climate change, so this will cause the subsequent analysis to underestimate the health-related welfare costs. On the other hand, the second subsection highlighted that our empirical strategy of utilizing inter-annual variation in weather will overestimate the measurable health-related welfare costs, relative to the costs due to permanent changes in temperature (unless the degree of climate change is "small"). This is because the available set of adaptations in response to a year's weather realization is constrained.

III. Data Sources and Summary Statistics

To implement the analysis, we collected the most detailed and comprehensive data available on mortality, energy consumption, weather, and predicted climate change. This section describes these data and reports summary statistics. More details on the data sources are provided in the Data Appendix.

A. Data Sources

Mortality and Population Data. The mortality data is taken from the Compressed Mortality Files (CMF) compiled by the National Center for Health Statistics. The CMF contains the universe of the 72.3 million deaths in the US from 1968 to 2002. Importantly, the CMF reports death counts by race, sex, age group, county of residence, cause of death, and year of death. In addition, the CMF files also contain population totals for four age groups, which we use to calculate all-cause and cause-specific mortality rates. Our initial sample consists of all deaths occurring in the continental 48 states plus the District of Columbia.

The cause-specific mortality rates are used to probe the validity of the estimated relationship between the all-cause mortality rate and temperature. Specifically, we test for separate relationships between temperature and cardiovascular disease, neoplasms (i.e., cancers), respiratory disease, and motor-vehicle accidents.[8] The above review of the medical literature suggested that there are plausible pathophysiological channels through which temperature can affect rates of cardiovascular and respiratory related deaths. We are unaware of a plausible connection between temperature and neoplasms. It is

[8] In terms of ICD-9 Codes, the causes of deaths are defined as follows: Neoplasms = 140-239, Cardiovascular Diseases = 390-459, Respiratory Diseases = 460-519, and Motor Vehicle Accidents = E810-E819.

possible that temperature and precipitation affect the motor vehicle fatality rate through their impact on driving conditions, so ex ante predictions are ambiguous for this cause.

Energy Data. The energy consumption data comes directly from the Energy Information Administration (EIA) State Energy Data System (EIA 2006). These data provide state-level information about energy prices, expenditures, and consumption from 1968 to 2002. The data is disaggregated by energy source and end use sector. All energy data is given in British Thermal Units (BTU).

We used the database to create an annual state-level panel data file for total energy consumption by the residential sector, which is defined as "living quarters for private households". The database also reports on energy consumption by the commercial, industrial, and transportation sectors. These sectors are not a focus of the analysis, because they do not map well into the health production function model outlined in Section II. Further, factors besides temperature are likely to be the primary determinant of consumption in these sectors.

The measure of total residential energy consumption is comprised of two pieces: "primary" consumption, which is the actual energy consumed by households, and "electrical system energy losses". The latter accounts for about 2/3 of total residential energy consumption; it is largely due to losses in the conversion of heat energy into mechanical energy to turn electric generators, but transmission and distribution and the operation of plants also account for part of the loss. In the 1968-2002 period, total residential energy consumption increased from 7.3 quadrillion (quads) BTU to 21.2 quads, and the mean over the entire period was 16.6 quads.

Weather Data. The weather data are drawn from the National Climatic Data Center (NCDC) Summary of the Day Data (File TD-3200). The key variables for our analysis are the daily maximum and minimum temperature as well as the total daily precipitation.[9] To ensure the accuracy of the weather readings, we developed a rule to select the weather stations. Specifically, we dropped all weather stations

[9] Other aspects of daily weather such as humidity and wind speed could influence mortality, both individually and in conjunction with temperature. Importantly for our purposes, there is little evidence that wind chill factors (a non-linear combination of temperature and wind speed) perform better than simple temperature levels in explaining daily mortality rates (Kunst et al. 1994). In addition, there are relatively few weather stations that measure relative humidity. For example, only 308 stations measured relative humidity in July 2000. The corresponding figures for July 1990 and 1980 are 259 and 0, respectively. As such, the coverage of stations that record humidity is too sparse for our analysis. See Barreca (2008) for an examination of the relationship between humidity and mortality.

at elevations above 7,000 feet because they were unlikely to reflect the weather experienced by the majority of the population within a county. Among the remaining stations, we considered a year's readings valid if the station provided measurements for all days in that year. The average annual number of stations with valid data in this period was 2,837 and a total of 6,969 stations met our sample selection rule for at least one year during the 1968-2002 period. The acceptable station-level data is then aggregated at the county level by taking an inverse-distance weighted average of all the valid measurements from stations that are located within a 200 km radius of each county's centroid. The valid measurements from acceptable stations are weighted by the inverse of their squared distance to the centroid so that more distant stations are given less weight. This procedure yields a balanced panel of 3,074 counties with acceptable weather data that accounts for 99% of all deaths in the US from 1968 to 2002.

Climate Change Prediction Data. Climate predictions are based on two state of the art global climate models. The first is the Hadley Centre's 3rd Coupled Ocean-Atmosphere General Circulation Model, which we refer to as Hadley 3 (T. C. Johns et al. 1997; Pope et al. 2000). This is the most complex and recent model in use by the Hadley Centre. It is a coupled atmospheric-ocean general circulation model, so it considers the interplay of several earth systems and is therefore considered the most appropriate for climate predictions. We also use predictions from the National Center for Atmospheric Research's Community Climate System Model (CCSM) 3, which is another coupled atmospheric-ocean general circulation model (NCAR 2007). The results from both models were used in the 4th IPCC report (IPCC 2007).

Predictions of climate change from both of these models are available for several emission scenarios, corresponding to 'storylines' describing the way the world (population, economies, etc.) may develop over the next 100 years. We focus on the A1FI and A2 scenarios. These are "business-as-usual" scenarios, which are the proper scenarios to consider when judging policies to restrict greenhouse gas emissions. See the Data Appendix for more details on these scenarios.

We obtained daily temperature and precipitation predictions for grid points throughout the continental US from the application of A1FI scenario to the Hadley 3 model for the years 1990-2099 and

the A2 scenario to the CCSM 3 for the years 2000-2099. The Hadley model gives daily minimum and maximum temperatures, while the CCSM model reports the average of the minimum and maximum. Each set of predictions is based on a single run of the relevant model. The Hadley 3 predictions are available for grid points spaced at 2.5° (latitude) x 3.75° (longitude) and there are 89 (of the 153) located on land. The CCSM 3 predictions are available for grid points spaced at roughly 1.4° (latitude) x 1.4° (longitude) and there are a total of 416 on land in the US.

We calculate future temperature and precipitation realization in two ways. The first assigns each county a daily weather realization directly from the Hadley and CCSM predictions. Specifically, this is calculated as the inverse-distance weighted average among all grid points within a given distance from the county's centroid. In the case of the Hadley 3 A1FI predictions, a radius of 300 kilometers ensures that every county gets a valid prediction for each day. Due to the greater spatial resolution, the CCSM 3 A2 predictions only require a radius of 200 kilometers. Each county's end of century predicted climate is the simple average of the predicted weather realizations for the 2070-2099 period. The limitation of this approach is that there may be systematic model error that causes the predictions to be too high or too low.

The second method adjusts the Hadley 3 A1FI weather predictions for model error by comparing the model's predictions for the 1990-2002 period with the actual realizations from the weather station data. For example in the case of temperature, we calculate Hadley 3 model errors for each of the 365 days in a year separately for each county as the average difference between county by day of year specific average temperature from the weather station data and the Hadley 3 A1FI predictions during the 1990-2002 period. This county by day of year-specific error is then added to the Hadley 3 A1FI predictions to obtain an error-corrected climate change prediction. The main limitations of this approach are that the historical Hadley predictions are only available for some years (i.e., 1990-2002) that were hot by historical standards and thirteen years is a relatively short period to validate the model.

In the subsequent analysis, we focus on these Hadley 3 A1FI error-corrected predictions. However, we will also report estimates based on the Hadley 3 A1FI and CCSM 3 A2 predictions that are not corrected for model error. Again, it is impossible to derive error-corrected CCSM 3 A2, because historical predictions are unavailable. The Data Appendix provides more details on the climate

predictions.

Before proceeding, it is important to underscore that the validity of the paper's estimates of the impacts of climate change depend on the validity of the climate change predictions. The state of climate modeling has advanced dramatically over the last several years, but there is still much to learn, especially about the role of greenhouse gases on climate (Karl and Trenberth 2003). Thus, the Hadley 3 A1FI and CCSM 3 A2 predictions should be conceived of as two realizations from a superpopulation of models and scenarios. The sources of uncertainty in these models and scenarios are unclear, so it cannot readily be incorporated into the below estimates of the impacts of climate change. Nevertheless, the use of two sets of daily business as usual climate change predictions provides some sense of the variation.[10]

B. Summary Statistics

Mortality Statistics. Table 1 reports the average annual mortality rates per 100,000 by age group using the 1968-2002 CMF data. It is reported separately for all causes of death and for deaths due to cardiovascular disease, neoplasms (i.e., cancers), respiratory disease, and motor-vehicle accidents. These four categories account for roughly 76% of all fatalities, though the relative importance of each cause varies by age.

The all-cause and all-age annual mortality rate is 877.2 per 100,000, but there is tremendous heterogeneity across age categories. The all-cause annual mortality rate for infants is 1,162.1. After the first year of life, mortality rates are increasing in age but do not exceed the infant rate until the over 65 category where it is roughly 5.2%. Although it is not reported here, it is noteworthy that the male fatality rate exceeds the female one in all age categories.

As is well-known, mortality due to cardiovascular disease is the single most important cause of death in the population as a whole. Cardiovascular disease is responsible for 45.9% of overall mortality, even though it accounts for a relatively unimportant share at ages younger than 45. Respiratory diseases account for 6.8% of overall mortality.

[10] We are unaware of a single previous impact study that utilizes daily predictions from even a single model-scenario combination.

Weather and Climate Change Statistics. The analysis uses the rich daily historical weather and daily climate change predictions data to develop county-level measures of past and future weather. Table 2 reports on national and regional measures of observed temperatures from 1968-2002 and predicted temperatures from 2070-2099. For the observed temperatures, this is calculated across all county by year observations with non-missing weather data, where the weight is the total county population in the year. The predicted temperatures under climate change are based on the 2070-2099 predictions, where the weight is the average total county population over the years 1968-2002. Since these calculations of actual and predicted temperatures depend on the geographic distribution of the population in the US, systematic migration (e.g., from South to North) would change them without any change in the underlying climate.

The "Actual" column of Table 2 reports that the average daily mean is 56.4° F. This reflects the variation across all years and counties, as well as the within-year variation. The entries for the four Census regions reveal the geographical variation in this average. The average difference between the minimum and maximum is 21° F.[11] The table also reports that annual average precipitation is 39.4 inches.

Figure 2 depicts the average distribution of annual daily mean temperatures across ten temperature categories or bins, again during the 1968-2002 period. These categories represent daily mean temperature less than 10° F, greater than 90° F, and the eight 10° F wide bins in between. The height of each bar corresponds to the mean number of days that the average person experiences in each bin; this is calculated as the weighted average across county-by-year realizations, where the county-by-year's total population is the weight.[12] The average number of days in the modal bin of 60° - 70° F is 74.6. The mean number of days at the endpoints is 3.9 for the less than 10° F bin and 1.3 for the greater than 90° F bin.

These ten bins form the basis for our semi-parametric modeling of temperature in equations for

[11] For counties with multiple weather stations, the daily maximum and minimum are calculated as the average across the maximums and minimums, respectively, from each station.
[12] For a given county by year, the number of days in each bin is calculation ast the inverse-distance weighted aveage of the number of days in each bin at all weather stations within a 200 kilometer radius of the county centroid. This preservers the variation in temperatures, relative to assigning days to bins after averaging across mean temperatures from weather stations.

mortality rates and energy consumption throughout the remainder of the paper. This binning of the data preserves the daily variation in temperatures, which is an improvement over the previous research on the mortality impacts of climate change that obscures much of the variation in temperature.[13] This is important because there are substantial nonlinearities in the daily temperature-mortality and daily temperature–energy demand relationships.

The remaining columns of Table 2 report on the predicted changes in temperature from the three sets of climate change predictions for the 2070-2099 period.[14] The error-corrected Hadley 3 A1FI predictions indicate a change in mean temperature of 10.7° F or 5.9° Celsius (C). Interestingly, there is substantial heterogeneity as mean temperatures are expected to increase by 11.9° F in the Northeast and Midwest and a somewhat less 9.2° F in the West. The non-error-corrected Hadley 3 A1FI and CCSM 3 A2 predictions indicate increases in mean temperatures of 7.9° F and 6.6 ° F, respectively.[15]

Figure 3 provides an opportunity to understand how the full distributions of daily mean temperatures are expected to change. The most important changes in the distribution are in the last two bins. The Hadley 3 A1FI error-corrected predictions indicate that the typical person will experience 49.5 additional days per year where the mean daily temperature is between 80° F and 90° F. Equally surprising is that the mean daily temperature is predicted to exceed 90° F for 30.9 additional days per year.[16] To put this in perspective, the average person currently experiences 28.7 days in the 80° - 90° F range and just 1.3 days per year where the mean exceeds 90° F. The figure also reports on the change in the distribution of daily temperatures from the CCSM 3 A2 predictions.

An examination of the remainder of the figure highlights that the reduction in extreme cold days is much smaller than the increase in extreme hot days. The subsequent analysis demonstrates that this has

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[13] For example, Martens (1998) and Tol (2002a) use the maximum and the minimum of monthly mean temperatures over the course of the year.

[14] For comparability, we follow much of the previous literature on climate change and focus on the temperatures predicted to prevail at the end of the century.

[15] The fourth and most recent IPCC report summarizes the current state of climate change predictions. This report says that the doubling of carbon dioxide concentrations is "likely" (defined as $P > 66\%$) to lead to an increase of average surface temperatures in the range of 2° to 4.5° C with a best estimate of 3° C (IPCC 4 2007). Thus, the predictions in Table 2 are at the high end of the likely temperature range associated with a doubling of carbon dioxide concentrations.

[16] We emphasize that a mean daily temperature of 90° F is very hot. For example, a day with a high of 100° F would need a minimum temperature greater than 80° F to qualify.

a profound effect on the estimated impacts of climate change on mortality and energy consumption.

Returning to Table 2, the bottom panel reports on temperatures for days when the mean exceeds 90° F. The paper's primary econometric model for mortality assumes that the impact of all days in the greater than 90° F bin have an equal impact. The predicted increase in mean temperatures among days in this bin is relatively modest, with predicted increases of 4.2° F from the error-corrected Hadley 3 A1FI and 4.3° F and 1.8° F for the other two sets of predictions. Consequently, historical data are likely to be informative about the impacts of the additional days with temperatures exceeding 90° F.

IV. Econometric Strategy

This section describes the econometric models for annual mortality rates and residential energy consumption.

A. Mortality Rates.

We fit the following equation:

$$(5)\ Y_{cta} = \sum_j \theta_{aj}^{TMEAN} TMEAN_{ctj} + \sum_l \delta_{al}^{PREC} PREC_{ctl} + \alpha_{ca} + \gamma_{sta} + \varepsilon_{cta},$$

where Y_{cta} is the mortality rate for age group a in county c in year t. In the subsequent analysis, this equation is estimated separately for four separate age groups (ages 0-1, 1-44, 45-64, and 65+) so that all parameters are allowed to vary across these age groups. The last term in equation (5) is the stochastic error term, ε_{cta}.

The variables of interest are the measures of temperature and precipitation. They are constructed to capture the full distribution of annual fluctuations in weather. The variables $TMEAN_{ctj}$ denote the number of days in county c and year t where the daily mean temperature is in the j^{th} of the ten bins used in Figures 2 and 3. Thus, the only functional form restriction is that the impact of the daily mean temperature on the annual mortality rate is constant within 10° F degree intervals.[17] The choice of ten temperature bins represents an effort to allow the data, rather than parametric assumptions, to determine

[17] Schlenker and Roberts (2006) also consider a model that emphasizes the importance of nonlinearities in the relationship between crop yields and temperature.

the mortality-temperature relationship, while also obtaining estimates that are precise enough that they have empirical content. This degree of flexibility and freedom from parametric assumptions is only feasible because we are using 35 years of data from the entire US. The variables $PREC_{ctl}$ are simple indicator variables based on annual rainfall in county c in year t. Each indicator corresponds to a 5-inch bin and there are 11 of them, ranging from less than 10 inches to more than 60 inches.

The equation includes a full set of county-by-age group fixed effects, α_{ca}, which absorb all unobserved county-specific time invariant determinants of the mortality rate for each age group. So, for example, differences in permanent hospital quality or the overall healthiness of the local age-specific population will not confound the weather variables. The equation also includes state-by-year effects, γ_{sta}, that are allowed to vary across the age groups. These fixed effects control for time-varying differences in the dependent variable that are common across counties within age groups in a state (e.g., changes in state Medicare policies).

The validity of this paper's empirical exercise rests crucially on the assumption that the estimation of equation (5) will produce unbiased estimates of the θ_{aj}^{TMEAN} and δ_{al}^{PREC} vectors. By conditioning on the county and state-by-year fixed effects, these vectors are identified from county-specific deviations in weather about the county averages after controlling for shocks common to all counties in a state. Due to the unpredictability of weather fluctuations, it seems reasonable to presume that this variation is orthogonal to unobserved determinants of mortality rates. For example in the case of the j[th] temperature variable, we believe the identifying assumption E[$TMEAN_{ctj}$ ε_{cta} | $TMEAM_{ct-j}$, $PREC_{ctl}$, α_{ca}, γ_{sta}] = 0 is valid.

There are two further issues about equation (5) that bear noting. First, it is likely that the error terms are correlated within county by age groups over time. Consequently, the paper reports standard errors that allow for heteroskedasticity of an unspecified form and that are clustered at the county-by-age group level. Second, we fit weighted versions of equation (5), where the weight is the square root of the age group's population in the county (i.e., the denominator) for two complementary reasons. The estimates of mortality rates from large population counties are more precise, so it corrects for heteroskedasticity associated with these differences in precision. Further, the results reveal the impact on

the average person, rather than on the average county, which we believe is more meaningful.

Before turning to models for energy consumption, it is important to explain why the dependent variable is the annual mortality rate, rather than the daily mortality rate as in Deschênes and Moretti (2007). With unlimited data, the estimation of a daily mortality equation could flexibly capture the dynamic relationship between mortality and temperature. However, such an equation is extremely demanding of the data, because capturing the dynamic effects of temperature requires including many lags of the temperature variables and it is desirable to model temperature flexibly. For example, a model that includes the temperatures in the 50 previous days and uses equation (5)'s ten temperature bins would require the estimation of 500 separate temperature parameters. If the dynamic relationship between temperature and mortality persists for a year, then it would be necessary to estimate 3,650 temperature parameters! Furthermore, daily mortality data for the entire U.S. is only available from 1972-1988, and there may be insufficient variation in temperature within this relatively short period of time to precisely identify some of the very high and very low temperature categories.

Although equations for annual mortality are less elegant, they may still solve the problems of forward displacement and delayed impacts. In particular, this approach means that every fatality is a function of the daily temperature realizations for all previous days within the same year. Its potential weakness is that fatalities in the early part of the year may be caused by temperature realizations in the preceding year, but equation (5) only includes temperature realization in the current year. In the below, we find that models that include the current and previous year's temperature variables produce estimated impacts of climate change that are qualitatively similar to those based on equation (5) that only include the current year's weather realization. Therefore, we believe this approach approximately captures the full long-run impact of a day with a temperature in the relevant range.

Residential Energy Consumption. We fit the following equation for state-level residential energy consumption:

(6) $$\ln(C_{st}) = \sum_j \theta_j^{TMEAN} TMEAN_{stj} + \sum_l \delta_l^{PREC} PREC_{stl} + X_{st}\beta + \alpha_s + \gamma_{dt} + \varepsilon_{st}.$$

C_{st} is residential energy consumption in state s in year t, and d indexes Census Division. The modeling of temperature and precipitation is identical to the approach in equation (5). The only difference is that these variables are measured at the state-by-year level—they are calculated as the weighted average of the county-level versions of the variables, where the weight is the county's population in the relevant year. The equation also includes state fixed effects (α_s) and census division-by-year fixed effects (γ_{dt}) and a stochastic error term, ε_{st}.

The vector X_{st} includes the state-level ln of population and gross domestic product and their squares. The former variable accounts for differences in population growth within a Census Division that might confound the consistent estimation of the θ_j's.[18] The latter is included because energy consumption is a function of income.

Finally, we will also report the results from versions of equation (6) that model temperature with heating and cooling degree days. We follow the consensus approach and use a base of 65° F to calculate both variables.[19] To implement this alternative method for modeling a year's temperature, we sum the number of heating and cooling degree days separately over the year.[20] We then include the number of heating and cooling degree days and their squares in equation (6) instead of the $TMEAN_{stj}$ variables.

V. Results

[18] For example, Arizona's population has increased by 223% between 1968 and 2002 compared to just 124% for the other states in its Census Division. This poses a challenge, because its high temperatures mean that it plays a disproportionate role in the identification of the θ_j's associated with the highest temperature bins. In fact, we estimated state-by-year regressions for the number of days where the mean temperature was in the > 90° F bin that adjusted for state fixed effects and census division-by-year fixed effects. The mean of the annual sum of the absolute value of the residuals for Arizona is 3.6 but only 0.6 in the other states in its Census Division (i.e., Colorado, Idaho, New Mexico, Montana, Utah, Nevada, and Wyoming).

[19] Electrical, natural gas, power, heating, and air conditioning industries utilize heating and cooling degree calculations to predict demand (http://www.fedstats.gov/qf/meta/long_242362.htm). Further, the National Oceanic and Atmospheric Administration recommends using a base of 65° F for both heating and cooling degree days (http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/ddayexp.shtml). Further, an examination of the figures in Engle et al.'s seminal paper on the relationship between temperature and electricity sales suggests that 65° F is a reasonable base for both cooling and heating degree days (Engle et al. 1986).

[20] Specifically, on a given day, the number of cooling degree days equals the day's mean temperature (i.e., the average of the minimum and maximum) minus 65° F for days where the mean is above 65° F and zero for days when the mean is below 65° F. Analogously, a day's heating degree days is equal to the absolute value of 65° F minus its mean for days where the mean is below 65° F and zero otherwise. So, a day with a mean temperature of 72° F would contribute 7 cooling degree days and 0 heating degree days, while a day with a mean of 51° F would contribute 0 cooling degree days and 14 heating degree days.

This section is divided into three subsections. The first explores the extent of variation in the temperature variables in the context of the rich statistical models that we employ. The second provides estimates of the impact of predicted climate change on the mortality rates of specific age groups and the overall population. The third examines the impact of predicted climate change on residential energy consumption.

A. How Much Variation is there in Temperature?

The preferred specifications model temperature with ten separate variables. The success of this modeling choice requires substantial inter-annual variation in county-level temperatures after adjustment for county and state-by-year (or census division-by-year) fixed effects.

Figure 4 depicts the extent of inter-annual variation in temperature. For each daily mean temperature bin, we create a data file where the observations are from all county-by-year observations with valid weather data between 1968 and 2002. We then regress the annual realization of the number of days in the temperature bin against state-by-year and county fixed effects. For each county-by-year, we sum the absolute value of the residuals. This sum is the average number of days in a county-by-year available to identify the parameter associated with that temperature bin after adjustment for the fixed effects. The figure reports the mean of this number across all county-by-year observations.

An inspection of the figure reveals substantial variation in temperatures. The residual variation is greatest for the temperature variables between 20° F and 90° F. Although the mean of the absolute value of the residuals for the >90° F bin is 0.5 days, the size of our data file helps greatly. Since there are 107,590 county-by-year observations (and thus a total of 39,270,350 county-by-day observations), this means that there are roughly 53,795 days to identify the impact of a day in this bin. The analogous figure for the 80°-90° F bin is 387,324 days. We conclude that there is enough residual variation in the data to proceed with this semi-parametric approach. Indeed, the subsequent standard errors support this conclusion.

B. Estimates of the Impact of Climate Change on Mortality

All Cause Mortality Results. Figure 5 provides an opportunity to better understand the paper's approach. Specifically, it plots weighted sums of the regression coefficients (i.e., $\hat{\theta}_{aj}^{TMEAN}$) from the estimation of the four age group-specific regressions, where the weights are the population shares in the four age groups. In each of these regressions, the $TMEAN_j$ variable associated with the 50°-60° F bin was dropped, so each θ_j measures the estimated impact of an additional day in bin j on the mortality rate (i.e., deaths per 100,000), relative to the impact of a day in the 50° - 60° F range. The figure also plots the estimated θ_j 's plus and minus two standard errors, so their precision is evident.

It is evident that mortality risk is highest at the coldest and hottest temperatures. Indeed, the response function between mortality and temperature has a U-shape, albeit a somewhat flattened one. For example, the mean of the coefficients associated with the three lowest temperature categories is 0.58, so exchanging a single day in this range for one in the 50°-60° F range would lead to 0.58 fewer annual deaths per 100,000. The largest coefficient is the one associated with the > 90°F temperature bin and it is 0.83. It is noteworthy that the null of equality with the base category can be rejected at conventional significance levels for these hot and cold extreme temperatures, even though there are relatively few days to identify the coefficients. Finally, the coefficients associated with the temperatures in the middle range are all smaller in magnitude, and it is frequently impossible to reject the null of equality with the base category.

The revealed mortality-temperature relationship can be combined with any predictions about climate change to develop estimates of mortality impacts. For example, a change in climate that shifted days from the < 30° F categories to the middle ones would lead to a reduction in the annual mortality rate. It is also possible to envision climate change scenarios where the mortality reductions due to reductions in extremely cold days are balanced by mortality increases from increases in extremely hot days for a zero net effect.

Figure 3 demonstrated that the state of the art climate models predict dramatic increases in the number of days in the two highest temperature bins, especially the > 90° F bin. Further, these increases are largely predicted to be offset by decreases in the number of days in the middle of the temperature distribution where mortality rates are the lowest. Under these scenarios, the US will exchange relatively

low mortality days for high mortality ones.

We now turn to a more precise calculation of the predicted mortality impacts of climate change. Table 3 summarizes the results from the estimation of separate versions of equation (5) for the four age groups using the error-corrected Hadley 3 A1FI predictions. Here and throughout the rest of the analysis (except Table 8), the climate change predictions are for the end of the century and this is defined as the average of the predictions for the years 2070-2099. The final row sums the estimated impacts to provide all age estimates.

The entries are based on calculations of the estimated impact of the climate change scenarios on annual US mortality for each age group. For example, the estimated impact of predicted temperature changes on a given county and age group is calculated as follows:

$$(7)\ M_{ca} = MeanPopulation_{ca} \times \sum_{j} (\hat{\theta}_{aj}^{TMEAN} \bullet \Delta TMEAN_{aj})$$

That is, the predicted change in the number of days in each temperature cell ($\Delta TMEAN_{cj}$) is multiplied by the corresponding age-group specific impact on mortality ($\hat{\theta}_{aj}^{TMEAN}$) and then these products are summed. This sum is then multiplied by the average population for that age group in that county ($MeanPopulation_{ca}$) over the sample period. The impacts for a given age group are then summed over all counties. This sum is the national age group-specific estimate of the change in annual mortality. It is straightforward to calculate the standard error (reported below the estimate in parentheses), since the estimated mortality change is a linear function of the parameters.

Columns (1a) – (1c) report this calculation for the bottom three temperature categories (i.e., < 10° F, 10° - 20° F, and 20° - 30° F), middle five, and top two (i.e., 80° - 90° F and > 90° F). Column (2) reports the total temperature impact and column (3) adds in the impact of the relatively inconsequential change in precipitation (which is calculated analogously to the method outlined in equation (7)). Column (4) reports the estimated percentage change in the annual mortality rate (and its standard error), which is calculated as the ratio of the change in the age group's annual mortality rate due to predicted climate change to its overall annual mortality rate.

Column (5) reports the change in life-years due to predicted climate change for each age

category. This entry is the product of the predicted change in annual fatalities and the residual life estimate for each age group, which is evaluated in the middle of the age range and taken from the 1980 Vital Statistics[21]; the negative values correspond to losses of life-years. This calculation may overstate the change in life-years, because affected individuals are likely to have shorter life expectancies than the average person. Nevertheless, these entries provide a way to capture that fatalities at young ages may have greater losses of life expectancy than those at older ages.

The error-corrected Hadley 3 A1FI results suggest that climate change would lead to approximately 38,000 additional deaths annually in the US (see the bottom row), which is equivalent to a 1.8% increase in the annual mortality rate.[22] It is important to underscore that the null hypothesis of a zero effect cannot be rejected at conventional significance levels. The life-years approach implies an annual loss of roughly 1.85 million life-years.

Three other findings bear highlighting. First, the predicted increase in the annual mortality rate is greatest for infants; the estimates suggest a 6.2% increase in the infant mortality rate or 2,600 additional infant deaths per year. This result is not surprising, because infants' thermoregulatory system is not yet fully functional (Knobel and Holditch-Davis 2007). Second, the estimated impacts on the other age categories are smaller and less robust statistically. Third, the reduction in cold days reduces mortality rates for all age categories. However, on average, this effect is markedly smaller than the jump in mortality associated with the increase in days exceeding 80° F, particularly the number of days exceeding 90° F.

Robustness Analysis. Table 4 reports the estimated impact of climate change on the all-age mortality rate from a series of alternative specifications. The intent is to probe the robustness of the results in Table 3. Column (1) uses error-corrected Hadley 3 A1FI predictions. Columns (2) and (3) use the non-error-corrected Hadley 3 A1FI and CCSM 3 A2 predictions.

Panel A reports the baseline all age estimates, which are derived from the estimation of the age-specific versions of equation (5), as in Table 3. These entries provide a basis of comparison for the

[21] The residual life estimates for the four age categories are 73.9 (infants), 53.6 (1-44), 24.7 (45-64), and 9.4 (> 65).
[22] We also estimated separate equations for cause-specific mortality rates. Approximately, half of the overall mortality impact results from increased fatalities to cardiovascular diseases.

remainder of the table. It is noteworthy that the non-error-corrected Hadley 3 A1FI estimated impact on the mortality rate of 4.7% is roughly 160% larger than the error-corrected one. This is largely because the non-error corrected Hadley 3 model predicts 52.5 additional days with a temperature greater than 90° F, compared to the 30.9 extra days from the error-corrected predictions.

Panel B reports on several changes to the baseline specification. In row 1, the models are estimated separately for men and women. The row 2 specification replaces the state-by-year fixed effects with year fixed effects. The ln of the mortality rate is the dependent variable in row 3, which means that across the four age groups a total of 19,308 observations are dropped since the ln of zero is not defined.

The approach of modeling temperature with the ten bins restricts the impact of any day with a temperature above 90° F to be the same. However, Figure 5 suggested that the mortality-temperature gradient was increasing in temperature, so the baseline approach may understate the estimated mortality impacts of climate change. We experimented with models that include a separate variable for the number of days with a temperature exceeding 100° F, but this was too demanding of the data and the estimated parameter associated with this variable had little empirical content (the 95% confidence interval was -3.18 to 5.81). As a more parametric alternative, row 4 presents the results from a specification that replaces the temperature variables with linear terms in cooling degree days (base 90° F) and heating degree days (base 20° F). These bases were chosen through inspection of the mortality-temperature response function in Figure 5.

The remaining rows experiment with alternative methods to model temperature. In rows 5 and 6, the specifications include 20 separate temperature variables: row 5 uses two separate sets of the same ten temperature bins for the daily maximum and minimum temperatures, respectively, while row 6 uses separate sets of the ten temperature bins for the current and previous years' daily mean temperatures to allow for the possibility that equation (5) inadequately accounts for the dynamics of the mortality-temperature relationship. There is some evidence that individuals acclimate to higher temperatures over time, so consecutive days with high temperatures (i.e., heatwaves) may have a different impact on annual

mortality than an equal number of hot days that do not occur consecutively.[23] The row 7 specification adds a variable for the number of instances of 5 consecutive days of mean daily temperature above 90° F and its associated parameter is used in the calculations of the climate change impacts.

These alterations to the baseline specification fail to have a meaningful impact on the qualitative finding that climate change will only have a limited impact on the mortality rate. Some of them modestly increase the point estimate, while others decrease it. The null of a zero impact cannot be rejected for all but one of the column (1) estimates.

Climate change may affect relative prices and individuals' choices in ways that will change the response functions. As an alternative to a full-blown general equilibrium model that necessarily involves numerous unverifiable assumptions, Panel C uses the available data to assess whether such changes are likely to alter the paper's findings. Specifically, the row 1 estimates are based on a response function that is obtained by fitting equation (5) with post-1980 data. The intuition is that in these years medical technologies are more advanced and air conditioning is more pervasive. In row 2, the response function is estimated with data from the half of counties where the average number of days per year with a mean temperature above 80° F exceeds the national median (14 days per year). The idea is that individuals are likely to have undertaken a series of adaptations to protect themselves against high temperatures in these counties and these adaptations may resemble the ones that climate change will induce. In this respect, the resulting response functions may better approximate the long-run impacts of climate change on mortality. The entries in both rows reflect the application of the relevant response function to the full sample.

Both of these approaches lead to smaller estimated impacts of climate change that are smaller than or equal to the baseline estimates. Although the 95% confidence intervals of these estimates and the baseline ones overlap, the Panel C results suggest that longer run adaptation will modestly decrease the mortality impacts of climate change. that adaptation will lead to mortality impacts of climate change that are smaller than those in Panels A and B.

In summary, Tables 3 and 4 suggest that the predicted changes in climate at the end of the century

[23] For example Hajat et al. (2002) find that heat waves later in the summer have a smaller impact on mortality and morbidity than heat waves that occur earlier in the year. Further, according to medical convention, exercising adults acclimate to heat within 3-12 days (Armstrong and Dziados 1986).

will increase the US mortality rate modestly. Indeed, the preferred error-corrected Hadley 3 A1FI climate change predications suggest an increase that is statistically indistinguishable from zero.

Geographic Variation in the Estimated Impacts. Table 6 explores the distributional consequences of climate change across the country. The entries are based on the national response function from Table 3 and Figure 5. This response function is applied to the error-corrected Hadley 3 A1FI predictions. .Just as in all previous calculations, the predicted climate and current climate both vary at the county level.

The table reveals substantial heterogeneity in the estimated impacts of climate change on mortality rates. States that are already hot are predicted to have the largest increases in mortality rates. The predicted increases exceeds 3.5% and is statistically significant in 10 states; Texas (8.2%), Louisiana (7.0%, and Arizona (5.9%) have the largest estimated increases. Twenty-one states have predicted declines in the mortality rate, although none would be judged statistically significant.; the three biggest declines are in Vermont (-1.6%), New Hampshire (-1.8%), and Maine (-1.9%). This set of states has very cold winters and it is evident that the beneficial impacts of reductions in cold days exceeds the harmful consequences of the increase in hot days. More generally, the geographical heterogeneity underscores that climate change is likely to produce winners and losers, at least in terms of health impacts.

C. Estimates of Adaptation from Energy Consumption

We now turn to an analysis of the effect of inter-annual fluctuations in temperature on residential energy consumption. Specifically, this subsection reports on the fitting of versions of equation (6) to the state-by-year data on residential energy consumption from the EIA. Here, the baseline specification includes eleven temperature variables; the > 90° F bin is divided into two bins, 90° - 100° F and > 100° F. In contrast to the mortality equations, it is possible to obtain a meaningful estimate of the parameter associated with the > 100° F bin, and, as will be apparent below, it is important to allow for this extra category. Recall, the annual mean of residential energy consumption is 16.6 quads in this period.

Figure 6 plots the estimated θ_j 's from the specification that includes these eleven temperature variables. The coefficients report the estimated impact of an additional day in bin j on annual energy

consumption, relative to energy consumption on a day where the temperature is in the 50° - 60° F range. The figure also plots the estimated θ_j 's plus and minus two standard errors, so their precision is evident. The estimates are adjusted for the ln of population and state gross domestic product, their squares and interaction.

The figure is dominated by the dramatic jump in energy consumption associated with days where the temperature exceeds 100° F. In particular, a day in this temperature range is associated with an additional 0.267 quads of energy consumption, relative to a day in the 50° - 60° F range. To put this in context, the next two largest temperature categories have associated coefficients of 0.052 (<10° F) and 0.059 (90° - 100° F).

Overall, the response function has a U-shape so that the hottest and coldest days are the highest energy consumption ones (although this is partially obscured by the scale due to the > 100° F bin). For example, the response function is flat and precisely estimated for temperatures between 30° and 80° F; the five estimated θ_j 's all range between 0 and 0.018. Energy consumption turns up at temperatures above and below this range. Overall, the figure demonstrates that fewer cold days will reduce energy consumption, while additional days at the highest part of the temperature distribution will increase it.

Table 6 reports the impact of climate change on annual residential energy consumption from the estimation of two versions of equation (6) and the error-corrected Hadley 3 A1FI predictions. Row 1 reports on a specification where temperature is modeled with the eleven temperature bin variables used in Figure 6. In the row 2 specification, temperature is modeled with heating and cooling degree days (both use a base of 65° F) and their squares.

The temperature bin approach indicates a substantial increase in energy consumption of 5.5 quads or 33%.[24] The more standard, but more parametric, heating and cooling degree days approach suggests a smaller increase of 1.7 quads or 10%. In both models the decrease in cold days leads to reductions in energy consumption, but this decline is smaller than the increase on hot days. This finding was foreshadowed by Figures 3 and 6, which together revealed the dramatic increase in the predicted number

[24] As is evident from Figure 6, the data reject the restriction that energy consumption is equal on days when the temperature is in the 90°-100° F and > 100° F ranges. The predicted increases in the number of days in the 90° - 100° F and > 100° F bins from error-corrected Hadley 3 A1FI are 40.6 and 13.7, respectively.

of high energy consumption days.[25]

Table 7 is structured similarly to Table 4 and presents the subset of robustness checks relevant for energy consumption from that table. The estimated impacts based on climate change predictions from error-corrected Hadley 3 A1FI, non-error-corrected Hadley 3 A1FI, and non-error-corrected CCSM 3 A2 are presented in columns (1) – (3). The "a" columns report the estimates from modeling temperature with the eleven temperature bins and the "b" ones use cooling and heating degree days. The baseline estimates (from Table 6) are presented in Panel A.

The estimated impacts from the specification checks in Panel B are generally smaller than the baseline estimates. On the one hand, none of these estimates associated with the preferred climate change prediction in column (1a) would be judged statistically significant by conventional criteria. Further, the estimated impact from the model that includes separate temperature bins for the daily minimum and maximum temperature effect is noticeably smaller (i.e., an increase of 0.9% versus 5.3%), which was not the case in the mortality regressions. On the other hand, all of the estimates are within two baseline standard errors of the baseline estimate. Finally, we note that the non-error-corrected Hadley 3 A1FI estimated impacts tend to be larger than the error-corrected ones, while the non-error-corrected CCSM 3 A2 estimates are smaller.[26]

Panel C reports on the estimated impacts when the response function is obtained from subsamples where adaptations to hot weather are more likely to have taken place. Just as with the mortality estimates, the entries from these specifications are smaller than the baseline ones. Indeed, the point estimates are all smaller and in the preferred column (1l) about 60% smaller. Thus, these findings suggest that due to adaptation the long-run impact of climate change in energy consumption will be smaller than is indicated by the baseline ones.[27]

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[25] These findings are consistent with predicted increases in energy consumption from a study of California (Franco and Sanstad 2006). To the best of our knowledge, our estimates are the first ones that are based on data from the entire country.

[26] When temperature is modeled with the ten bin variables from the mortality equations, the estimated increases (standard errors) in energy consumption due to climate change are 3.2 (1.1) with error-corrected Hadley 3 A1FI, 1.9 (1.3) with non-error-corrected Hadley 3 A1FI, and 1.4 (0.7) with non-error-corrected CCSM 3 A2.

[27] Mansur, Mendelsohn, and Morrison (2007) and Mendelsohn (2006) estimate the relationship between energy consumption and temperatures in the cross-section. As the discussion in Section II highlighted, this approach will reveal the equilibrium relationship between energy consumption and temperature (in the absence of specification

VI. Interpretation

Optimal decisions about climate change policies require estimates of individuals' willingness to pay to avoid climate change over the long run. Previous research has suggested that human health is likely to be a big part of these costs. This section assesses the magnitude of the estimated impacts in the US and discusses some caveats to this exercise.

The central tendency of the baseline mortality estimates is that by the end of the 21st century, the overall mortality rate will increase by about 1.8% with the error-corrected Hadley 3 A1FI predictions. To put this estimate in some context, the US age adjusted death rate for both genders has decreased from 1,304.5 to 832.7 per 100,000 between 1968 and 2003, which is a decline of approximately 1% per year. Thus, even if the point estimates are taken literally, the climate change induced increase in mortality is roughly equivalent to losing just 2 years of typical improvement in longevity.

As an alternative, Table 9 presents the present discounted value of the expected welfare loss associated with predicted changes in climate during the 21st century. These calculations use daily temperature predictions from error-corrected Hadley 3 A1FI. Columns (1a) and (1b) present the predicted changes in life-years and energy consumption (measured in quads) over the periods 2010-2039, 2040-2069, 2070-2099, and 2010-2099. The standard errors are reported in parentheses below the estimated impacts.

The total loss in life-years is about 48 million life years between 2010 and the end of the century. The increase in energy consumption is roughly 107 quads. The changes in life-years and energy consumption are largest in the 2070-2099 period, because the predicted temperature changes are largest during these years.

Columns (2a) and (2b) monetize these changes with two different sets of assumptions. In column (2a), we assume the value of a life year is $100,000 and the cost of a quad of energy consumption is $7.6

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error). Consequently, this cross-sectional approach is useful in predicting equilibrium energy demand, but in the presence of fixed costs it is not informative about the impact of climate change on energy related expenditures.

billion.[28] The calculations in column (2b) are based on the assumptions that real per capita income grows by 2% per year and the elasticity of the value of a life-year with respect to income is 1.6, which is consistent with Costa and Kahn (2004). Further, we assume that real energy prices increase by 5% annually. Thus, the current valuations of $100,000 per life year and $7.6 billion per quad increase such that the respective valuations are approximately $1,032,000 per life year and $863.3 billion per quad in 2099. In both columns, we assume a discount rate of 3%.

Column (2a) indicates that the present discounted values of these climate change induced losses over the remainder of the 21st century are about $900 billion with the error-corrected Hadley 3 A1FI predictions. This is equivalent to 6.8% of 2006 GDP. It is noteworthy though that this estimate has an associated t-statistic of roughly 1.1, so the null of zero damages cannot be rejected at conventional significance levels. The losses with the non-error-corrected Hadley 3 A1FI and CCSM 3 A2 predictions are larger; they are $3.2 trillion and $1.7 trillion, respectively, and the null of zero would be rejected in both cases.

The entries in columns (2b) are necessarily larger, which highlights that these calculations are sensitive to the assumptions about the evolution of the value of a statistical life-year and energy prices (as well as the discount rate). A judgment about the magnitude of these larger estimates requires decisions on the present value of future income growth. For this reason, we emphasize the column (2a) estimates.

There are a number of caveats to these calculations, and to the analysis more generally, that bear noting. First, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that the climate change predictions are correct, relative prices (e.g., for energy and medical services) will remain constant, the same energy and medical technologies will prevail, and the demographics of the US population (e.g., age structure) and their geographic distribution will remain unchanged. These assumptions are strong, but their benefit is that they allow for a transparent analysis that is based on the available data rather than on unverifiable assumptions.

Second, the life-years calculation assumes that the individuals whose lives are affected by the

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[28] This valuation of a life year is roughly consistent with Ashenfelter and Greenstone's estimate of the value of a statistical life. The average cost of a quad in 2006$ between 1990 and 2000 is $7.6 billion.

temperature changes had a life expectancy of 78.6 for women and 71.2 for men. It seems plausible and perhaps even likely that the individuals that die due to higher temperatures had below average life expectancies, in which case the estimated loss of life-years is too high.

Third, these calculations are unlikely to capture the full impact of climate change on health. In particular, there may be increases in the incidence of morbidities due to the temperature increases. Additionally, there are a series of indirect channels through which climate change could affect human health, including greater incidence of vector borne infectious diseases (e.g., malaria and dengue fever). Further, it is possible that the incidence of extreme events would increase, and these could affect human health (Emanuel 2005). However, this study is not equipped to shed light on these issues.

Fourth, the theoretical section highlighted that our estimates likely overstate the increase in mortality and energy consumption due to climate change. Our identification strategy relies on inter-annual fluctuations in weather, rather than a permanent change. There are a number of adaptations that cannot be undertaken in response to a single year's weather realization. For example, permanent climate change is likely to lead to some migration (presumably to the North), and this will be missed with our approach. Although these adaptations may be costly, individuals will only undertake them if they are less costly than the alternative. For this reason, our approach is likely to overstate the part of the health costs of climate change that we can estimate.

VII. Conclusions

There are several broader implications of this research. First, the age group-specific mortality and residential energy consumption response functions are not specific to any climate model. In fact, as global climate models advance and new climate change predictions emerge, the resulting predictions can be applied to this paper's response functions to obtain updated estimates of the mortality and energy impacts of climate change.

Second, the production of many types of energy involves the release of greenhouse gases. Thus, the finding of increased residential energy consumption suggests that climate modelers should account for this feedback between higher temperatures and greater greenhouse gas emissions that lead to yet higher

temperatures. Current climate models generally fail to account for this feedback loop.

Third, this paper has demonstrated that it is possible to develop harvesting and delayed-impact resistant estimates of the impacts of weather on mortality by combining annual mortality data and daily weather data. In principle, this approach can be applied to other settings where there is an unknown dynamic relationship between environmental exposure and human health. For example, a number of commentators have questioned whether the documented relationship between daily air pollution concentrations and daily mortality rates largely reflects harvesting.

Finally, the impacts of climate change will be felt throughout the planet. This paper's approach can be applied to data from other countries to develop estimates of the health related welfare costs of climate change elsewhere. It is especially important to develop estimates for countries where current temperature are higher than in the US and/or people are poorer and less able to afford life-preserving adaptations like increased energy consumption. Ultimately, the development of rational climate policy requires knowledge of the health and other costs of climate change from around the world, not just the US.

Data Appendix

I. Hadley 3 Model

We downloaded the Hadley Climate Model 3 (Hadley 3) data from the British Atmospheric Data Centre (http://badc.nerc.ac.uk/home/), which provides a wealth of atmospheric data for scientists and researchers. Hadley Centre data appears on BADC thanks to the Climate Impacts LINK Project, a distributor of archived climate model output to researchers. The future climate predictions generated by the Hadley Centre were initially prepared for the International Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES). Daily climate predictions generated by the Hadley 3 model are available for all years from 1990 through 2099 and for several climate variables – we downloaded the predicted maximum and minimum temperatures and precipitation levels for each day during the years 1990-2099.

The Hadley 3 grid spans the entire globe; latitude points are separated by 2.5°, and longitude points are separated by 3.75°. We use the 89 gridpoints that fall on land in the contiguous United States to develop climate predictions for each county in the United States. Following the procedure used to create a complete daily temperature record for each US county between 1968 and 2002, we use inverse-distance weighted average to assign grid point predictions to counties. All grid points located in a pre-specified radius of a county's centroid are used to impute the climate prediction, with measurements from grid points located further away from the centroid receiving less weight. A radius of 300 kilometers ensures that every county gets a valid Hadley 3 prediction for every day between 1990 and 2099.

II. National Center for Atmospheric Research's Community Climate System Model 3

We downloaded the NCAR Community Climate System Model (CCSM) 3 data from the World Climate Research Programme's Coupled Model Intercomparison Project's data portal (https://esg.llnl.gov:8443/index.jsp), which aims to organize a variety of past, present, and future climate data from models developed across the world for use by researchers. Daily climate predictions generated by the CCSM3 model are available for all future years from 2000 to 2099 and for several climate variables – we downloaded the predicted mean temperatures and precipitation levels for each day during the years 2000-2099.

The CCSM3 grid spans the entire globe; latitude and longitude points are both separated by 1.4°. We use the 416 gridpoints that fall on land in the contiguous United States to develop climate predictions for the contiguous United States. Again, we use inverse-distance weighted average to assign grid point predictions to counties. All grid points located in a pre-specified radius of a county's centroid are used to impute the climate prediction, with measurements from grid points located further away from the centroid receiving less weight. A radius of 200 kilometers ensures that every county gets a valid CCSM3 prediction for every day between 2010 and 2099.

III. Emissions Scenarios

We utilize predictions from the application of the A1FI scenario to the Hadley 3 model. This scenario assumes rapid economic growth (including convergence between rich and poor countries) and a continued heavy reliance on fossil fuels. Given the abundant supply of inexpensive coal and other fossil fuels, a switch to alternative sources is unlikely without greenhouse gas taxes or the equivalent, so this is a reasonable benchmark scenario. This scenario assumes the highest rate of greenhouse gas emissions, so it is a worst case.

We also present results from the application of the A2 scenario to the CCSM 3. This scenario assumes slower per capita income growth but larger population growth. Here, there is less trade among nations and the fuel mix is determined primarily by local resource availability. This scenario is characterized as emphasizing regionalism over globalization and economic development over environmentalism. It is "middle of the road" in terms of greenhouse gas emissions, but it is still a business as usual scenario,

because it does not reflect policies to restrict emissions.

IV. EIA Energy Consumption Data

The consumption data is derived from several different reports and forms depending on energy source. Coal consumption data for most sectors comes from the EIA's Annual Coal Report; electric power sector coal use is the exception, coming instead from forms EIA-906 "Power Plant Report" and EIA-920 "Combined Heat and Power Plant Report". Natural gas consumption data comes from the EIA's Natural Gas Annual. Most petroleum data is the "product supplied" data found in EIA's Petroleum Supply Annual, with the exception again of electric power sector use, which is reported on EIA-906 and EIA-920. Solar, wind, geothermal, and most biomass energy use data is also reported on those forms. Residential and commercial use of biomass is reported on forms EIA-457 "Residential Energy Consumption Survey" and "Commercial Buildings Energy Consumption Survey". Nuclear electric power and other electricity data comes from the EIA Electric Power Annual. Finally, system energy losses and interstate flow are estimated in the State Energy Data System.

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Figure 1: Theoretical Relationship Between Household Annual Energy Expenditures and Ambient Temperature for a Given Level of Indoor Temperature

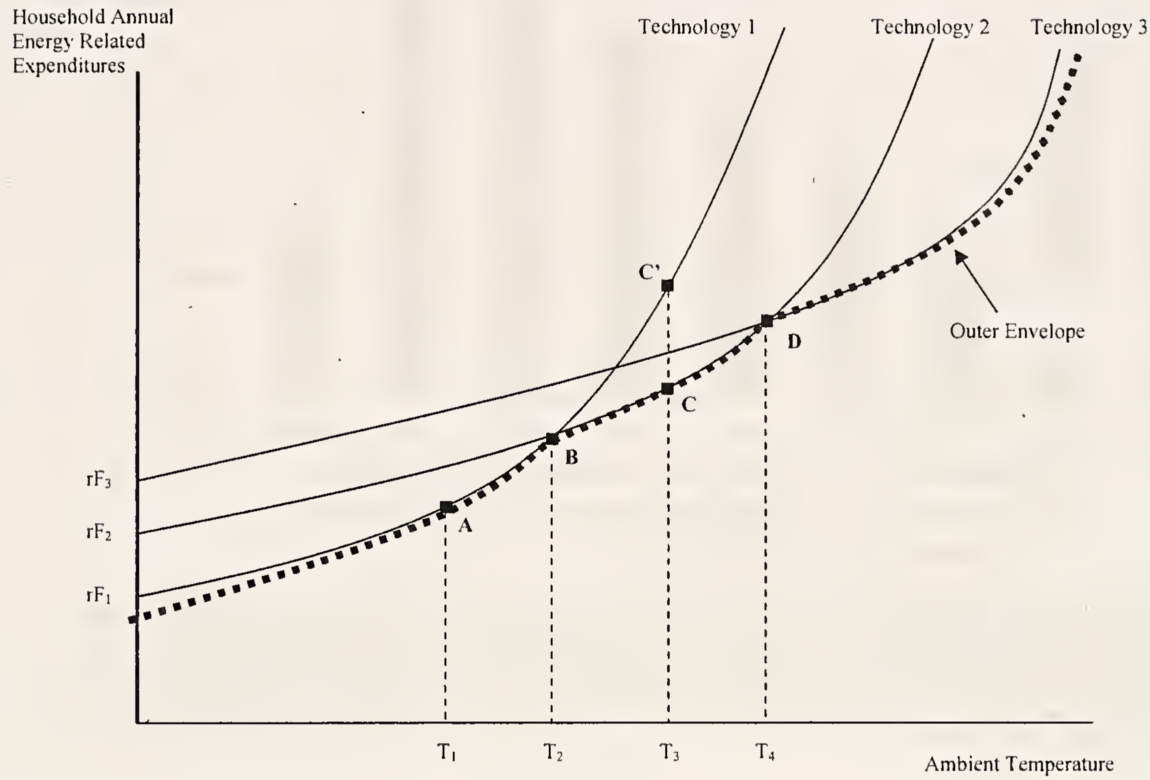
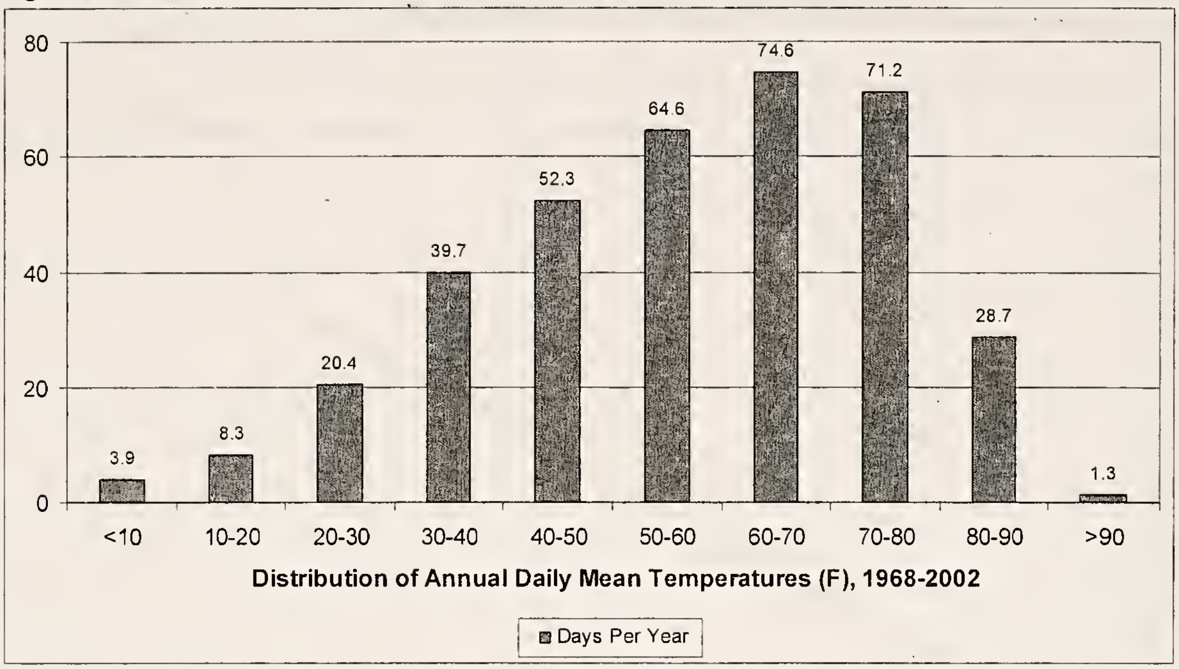
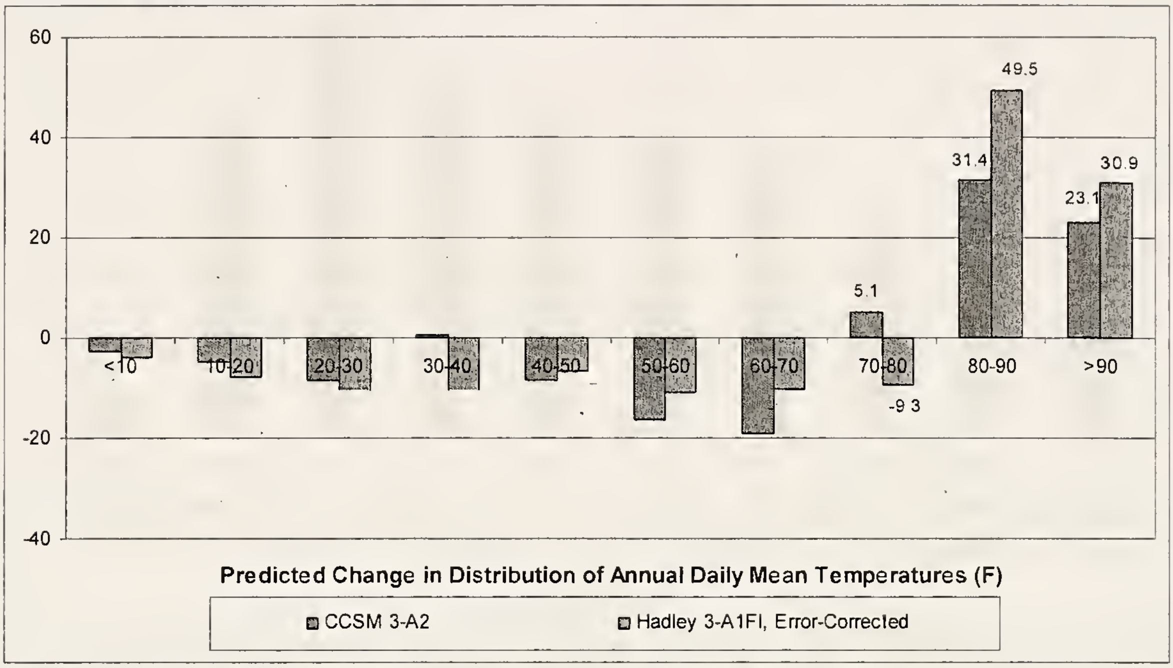


Figure 2: Distribution of Annual Daily Mean Temperatures (F), 1968-2002



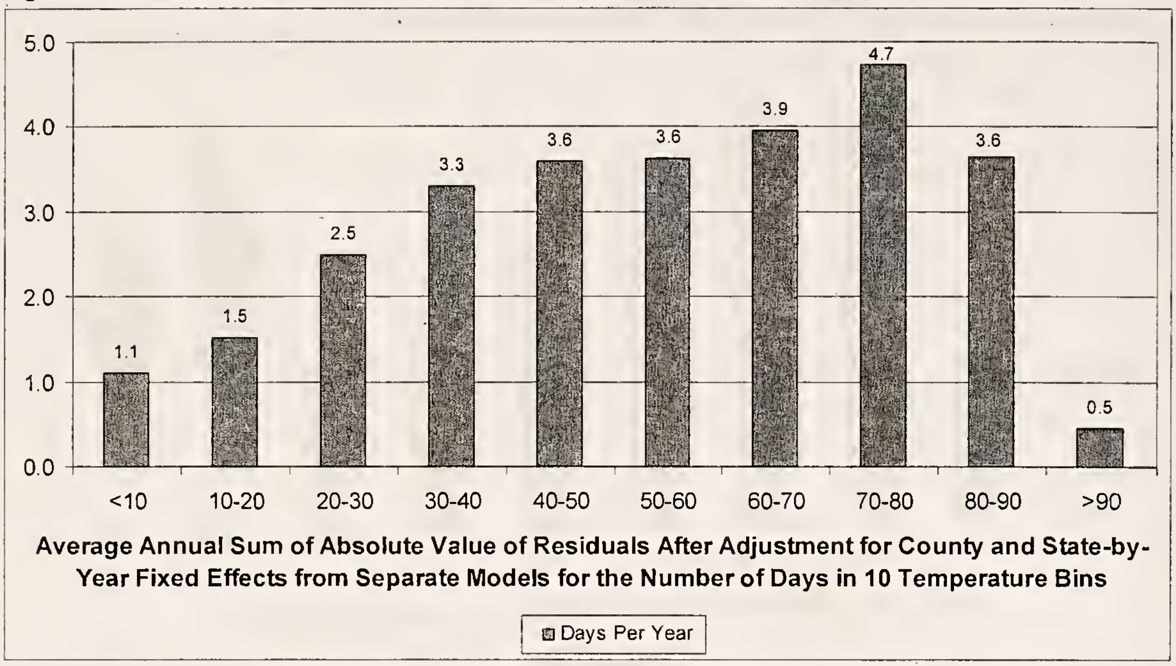
Notes: Figure 2 shows the distribution of daily mean temperatures across 10 temperature bins between 1968 and 2002. More specifically, each bar represents the average number of days per year in each temperature category for the 107,590 county-year observations in the sample, weighted by the total population in a county-year. The leftmost bin measures the number of days with a mean temperature less than 0° F and the rightmost bin is the number of days where the mean exceeds 90° F. The intervening 8 bins are all 10° F wide. The numbers above the bars correspond to the height of each bar.

Figure 3: Changes in Distribution of Annual Daily Mean Temperatures (F) Under The Error-Corrected Hadley 3, A1FI and CCSM 3, A2



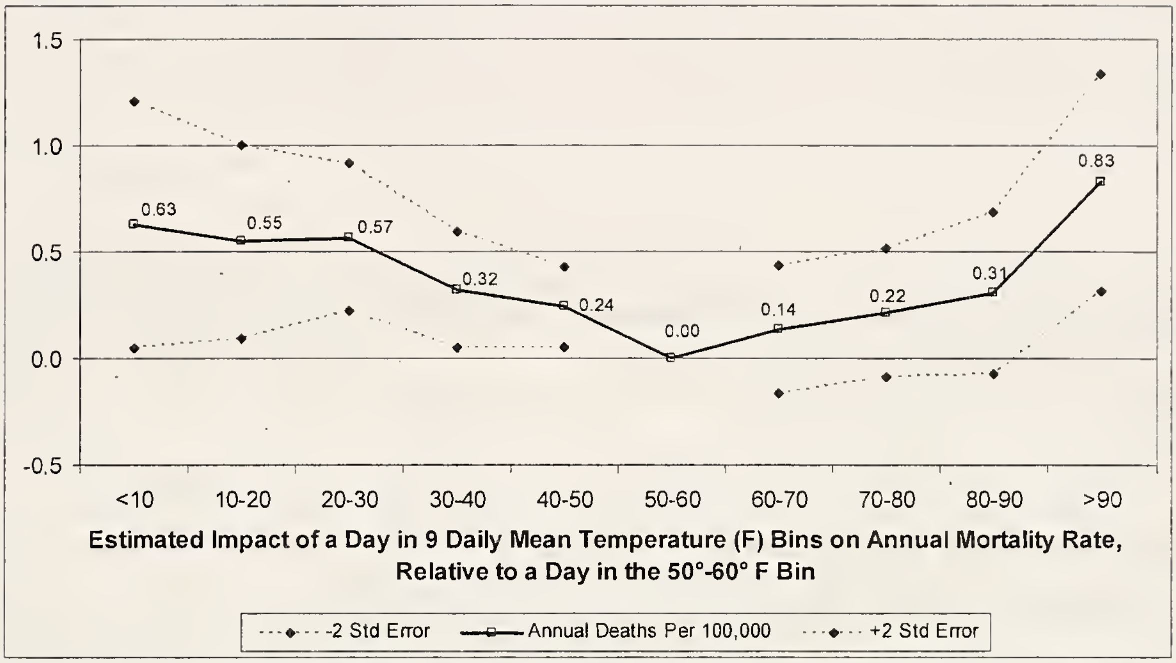
Notes: Figure 3 depicts the distribution of predicted changes in daily mean temperatures across the 20 temperature bins. More specifically, each bar represents the change in the average number of days per year in each temperature category. "Changes" are defined as the difference between the 1968-2002 average in each category and the 2070-2099 predicted average number of days in each category. Both averages are weighted by the average total population over 1968-2002 in a county. The temperature categories are defined as in Figure 2. The numbers above and below the bars correspond to the height of each bar.

Figure 4: Residual Variation in Annual Daily Mean Temperatures (F), 1968-2002



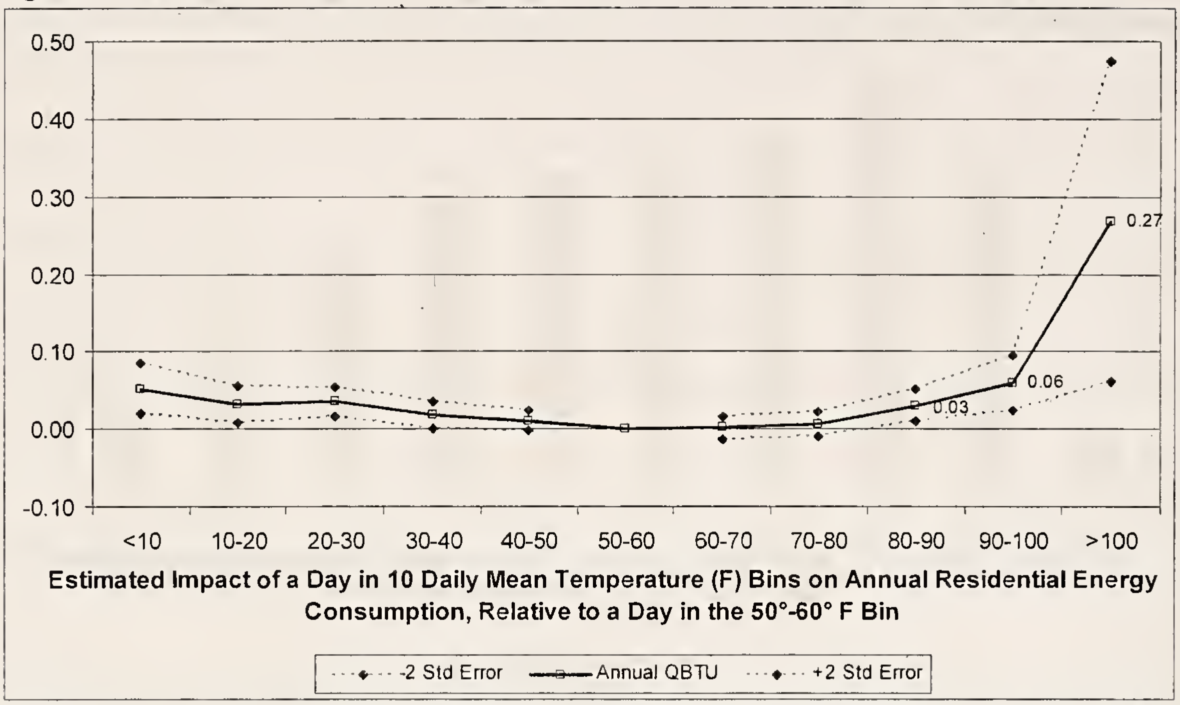
Notes: Figure 4 shows the extent of residual inter-annual variation in temperature. Each bar is obtained by first estimating a regression of the number of days in the relevant temperature category on unrestricted county effects and state-by-year effects, weighting by the total population in a county-year. For each county-year, we sum the absolute value of the residuals from the regression. The figure reports the mean of this number across all county by year observations. The resulting figures can be interpreted as the average number of days in a county by year that are available to identify the parameter associated with that temperature bin after adjustment for the fixed effects. The numbers above the bars correspond to the height of each bar.

Figure 5: Population-Weighted Sum of Regression Estimates Across Age Groups, (relative to temperature cell 50-60)



Notes: Figure 5 plots the aggregate response function between annual mortality rate (per 100,000) and daily mean temperatures. This is obtained by fitting equation (4) for the mortality rate in each age group. The age-group specific estimates are then combined into a single "aggregate" estimate by taking a weighted sum of the age-specific estimates, where the weight is the average population size in each age group. The response function is normalized with the 50°-60° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on the aggregate annual mortality rate (i.e., deaths per 100,000) relative to the mortality rate associated with a day where the temperature is between 50°-60° F. The figure also plots the estimated θ_j's plus and minus two standard error of the estimates. The numbers above the response function correspond to the point estimates associated with each temperature bin.

Figure 6: Estimated Impact on Total Energy Consumption in the Residential Sector



Notes: Figure 6 plots the estimated response function between aggregate residential energy consumption (in QBTU) and daily mean temperatures. This is obtained by fitting equation (6) on our sample of 1,715 state-year observations. The response function is normalized with the 50°-60° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on residential QBTU relative to the residential QBTU associated with a day where the temperature is between 50°-60° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates. The numbers above the response function correspond to the point estimates associated with each temperature bin.

TABLE 1: AVERAGE ANNUAL MORTALITY RATES PER 100,000 POPULATION, 1968-2002

Age Group:	All Causes of Death (1)	Cardiovascular Disease (2)	Neoplasms (3)	Respiratory Disease (3)	Motor-Vehicle Accidents (4)
Infants	1,162.1	23.7	4.6	51.6	---
1-44	114.0	14.3	15.3	2.8	1.3
45-64	865.0	332.9	278.9	38.3	13.3
65+	5,211.3	2,787.6	1,070.0	420.5	17.2
All Ages	877.2	403.0	191.3	59 5	14 9

Notes: Averages are calculated for a sample of 107,590 county-year observations. All entries are weighted averages, where the weight is population in the relevant demographic group in a county-year. The ICD-9 codes corresponding to the causes of deaths are defined as follows: Neoplasms = 140-239, Cardiovascular Disease = 390-459, Respiratory Disease = 460-519, Motor Vehicle Accidents = E810-E819.

TABLE 2: POPULATION-WEIGHTED AVERAGES OF DAILY MEAN TEMPERATURES ACROSS COUNTIES, 1968-2002

	Actual 1968-2002	Hadley 3, A1FI Error-Corrected 2070-2099		Hadley 3, A1FI 2070-2099		CCSM 3, A2 2070-2099	
	Level (1)	Level (2a)	Difference (2b)	Level (3a)	Difference (3b)	Level (3a)	Difference (3b)
Average Daily Mean (F)							
All Counties	56.4	67.1	10.7	64 3	7.9	63.0	6.6
Northeast Region	51.0	62.9	11.9	58 0	7 0	57.1	6 1
Midwest Region	50 0	61.8	11.9	60 0	10.1	59.8	9.8
South Region	63.2	73.2	10.0	72 1	8.9	69.0	5.8
West Region	58 8	68.0	9.2	63.1	4.3	63.3	4.5
Average Daily Minimum (F)							
All Counties	45 9	56 6	10 7	54 1	8.2	—	--
Average Daily Maximum (F)							
All Counties	66.9	77.7	10.8	74.5	7.6	—	---
Average Annual Precipitation (in)	39.2	46 1	6.9	44.7	5.5	34 1	-5.1
All Counties							
Days with mean >90F (All Counties)							
Average Daily Mean	92.7	96.9	4.2	97 0	4 3	94.6	1 8
Average Daily Minimum	79.4	83.0	3 6	83 1	3.7	—	--
Average Daily Maximum	106.0	110.8	4.8	110.8	4 8	—	--

Notes: Averages are calculated for samples of size 39,270,350 (column 1), and 33,660,300 (columns 2 and 3). These represent the 365 annual observations for the 3074 counties in the sample, over a 35 year period (column 1) or a 30 year period (columns 2 and 3). Averages are weighted by total county population in a given year (column 1) or the average total county population during 1968-2002 (columns 2 and 3).

TABLE 3: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL MORTALITY, ERROR-CORRECTED HADLEY 3, A1FI SCENARIO

Age Group:	Impact of Change in Days with Temperature <30F (1a)	30F-80F (1b)	>80F (1c)	Total Temperature Impact (2)	Temperature and Precipitation Impact (3)	% Change in Annual Mortality (4)	Annual Change in Life-Years (5)
Infants	-476.7	-618.0	3,764.7	2,670.0	2644.0	6.2	-195,337.7
	(560.2)	(439.8)	(1,673.4)	(1,424 7)	(1,438.6)	(3.4)	
1-44	-9,138.3	-9,436.8	26,391.4	7,816.3	7254.9	4.0	-388,864.7
	(3,256.3)	(4,805.8)	(9,978.7)	(6,937.5)	(7,042.3)	(3.9)	
45-64	-8,608.1	-5,719.0	17,441.9	3,114.9	2752.8	0.7	-67,855.8
	(2,306.1)	(2,018.5)	(6,190.9)	(4,682.7)	(4,800.6)	(1 2)	
65+	-24,389.9	-9,223.9	58,635.7	25,021.9	25,338.3	1.7	-239,193.1
	(6,774.7)	(4,804.0)	(20,638.6)	(14,599.0)	(14,847.9)	(1.0)	
All Ages	**-42,613.1**	**-24,997.7**	**106,233.7**	**38,622.9**	**37,989.9**	**1.8**	**-891,251.2**
	(12,897.3)	**(12,068.1)**	**(38,481.6)**	**(27,644.0)**	**(28,129.5)**	**(1.3)**	

Notes: The estimates are from fixed-effect regressions by age group. For each group there are 107,590 county-year observations. Each model includes county fixed-effects and state-by-year effects unrestricted for each age group. The dependent variable is the annual mortality rate in the relevant age group in a county-year. The regressions are weighted by the population count in the relevant age group in a county-year. Control variables include a set of 11 indicator variables capturing the full distribution of annual precipitations. Standard errors are clustered at the county-by-age group level. See the text for further details.

TABLE 4: ALTERNATIVE ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL MORTALITY RATES

	Hadley 3 A1FI, Error-Corrected (1)	Hadley 3 A1FI (2)	CCSM 3 A2 (3)
A. Baseline Estimates	**1.8**	**4.7**	**2.1**
	(1.3)	**(1.7)**	**(1.0)**
B. Alternative Specifications			
1. Separate Models for Females and Males	1.0	4.7	1.1
	(0.7)	(1.9)	(0.5)
2. Year Effects Only	1.3	3.1	1.4
	(1.0)	(1.9)	(1.4)
3. log (mortality rate) is Dependent Variable	1.2	4.3	1.5
	(1.5)	(1.9)	(1.1)
4. Model Temperature with Cooling and Heating Degree-Days (Base 90° F and 20° F)	1.6	7.2	2.8
	(0.9)	(3.4)	(1.4)
5. Ten Separate Variables for Daily Minimum and Maximum Temperature	1.4	3.7	---
	(0.9)	(1.3)	
6. Ten Separate Variables for Current and Previous Years' Temperatures	3.6	5.5	2.2
	(1.5)	(2.6)	(1.5)
7. Add Variable for Number of "Heatwaves"	1.4	3.7	1.6
	(1.4)	(1.9)	(1.0)
C. Using "Heat Resistant" Subsets of the Data to Infer Long Run Effects			
1. Sample Restricted to Post-1980 Data	1.8	3.8	2.0
	(1.4)	(1.7)	(1.1)
2. Sample Restricted to Counties Above the National Median in the Number of Days Exceeding 80° F	0.9	4.0	1.6
	(1.7)	(1.9)	(1.3)

Notes: The estimates are from fixed-effect regressions estimated separately by age group and then the age-specific estimated mortality impacts are summed across age groups. See the notes to Table 3 for more details. Specification B.1 is based on regressions estimated separately for females and males. Specification B.2 replaces the state by year fixed effects by year fixed effects. In model B.3, the dependent variable in the regressions is the log mortality rate. Specification B.4 is based on heating and cooling degree-days instead of temperature bins. Specification B.5 models temperature with two separate sets of the same 10 temperature bins for the daily maximum and minimum temperatures, respectively, while specification B.6 uses separate sets of the 10 temperature bins for the current year's daily mean temperature and the previous year's daily mean temperature to allow for the possibility that equation (5) inadequately accounts for the dynamics of the mortality-temperature relationship. Specification B.7 include controls for "heatwaves", which are defined as episodes of 5 consecutive days where the daily mean temperature exceeds 90° F (sample average = 0.9 such heatwaves per county-year). Specification C.1 estimates the models using data for 1980-2002 only. Finally, specification C.2 estimates the response function with data from the half of counties where the average number of days per year with a mean temperature above 80° F exceeds the national median (14 days). See the text for further details.

TABLE 5: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON STATE-LEVEL ANNUAL MORTALITY RATES (IN PERCENT), ERROR-CORRECTED HADLEY 3, A1FI SCENARIO

	Hadley 3, A1FI, Error-Corrected	
	Impact	(Std Error)
Texas	8.2	(3.3)
Louisiana	7.0	(2.6)
Arizona	5.9	(2.1)
Oklahoma	5.5	(2.4)
Mississippi	4.8	(1.9)
Arkansas	4.3	(1.8)
Alabama	4.2	(1.7)
South Carolina	3.8	(1.8)
Florida	3.8	(1.5)
Georgia	3.6	(1.6)
Kansas	3.5	(2.0)
California	3.1	(2.0)
Nevada	2.6	(1.6)
North Carolina	2.5	(1.5)
Tennessee	2.3	(1.4)
Missouri	2.2	(1.5)
Maryland	2.2	(1.6)
Delaware	2.1	(1.6)
Dist Columbia	2.0	(1.3)
Kentucky	1.7	(1.4)
Virginia	1.6	(1.3)
New Jersey	1.2	(1.4)
Nebraska	0.6	(1.6)
New York	0.4	(1.3)
Pennsylvania	0.4	(1.3)
New Mexico	0.2	(1.4)
Oregon	0.1	(1.2)
Washington	0.0	(1.3)
West Virginia	-0.2	(1.3)
Ohio	-0.2	(1.4)
Indiana	-0.2	(1.4)
South Dakota	-0.2	(1.8)
Iowa	-0.3	(1.6)
Illinois	-0.3	(1.4)
Idaho	-0.5	(1.5)
Minnesota	-0.5	(1.9)
Utah	-0.6	(1.6)
Connecticut	-0.8	(1.4)
Michigan	-0.9	(1.6)
North Dakota	-1.0	(2.1)
Massachusetts	-1.0	(1.3)
Rhode Island	-1.1	(1.3)
Montana	-1.1	(1.6)
Wisconsin	-1.3	(1.6)
Colorado	-1.4	(1.6)
Wyoming	-1.6	(1.7)
Vermont	-1.7	(1.6)
New Hampshire	-1.8	(1.5)
Maine	-1.9	(1.4)

Notes: The estimates of the response functions are from the Table 3 regressions. For each state, we calculate the predicted change in the distribution of daily temperatures by taking a population-weighted average of the county-specific predicted changes (see equation 7). The state-level predictions are then multiplied by the national estimates of the response function to obtain the state-level impacts on mortality. The impacts reported in Table 5 are presented as percent of annual deaths in each state.

TABLE 6: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL RESIDENTIAL ENERGY CONSUMPTION, ERROR-CORRECTED HADLEY 3, A1FI SCENARIO

	Impact of Change in Days with Temperature:			Impact of Change in:		Temperature Impact	Precipitation & Temperature Impact	% Change
	<30° F	30° - 80° F	> 80° F	Heating Degree Days	Cooling Degree Days			
	(1a)	(1b)	(1c)	(1d)	(1e)	(2)	(3)	(4)
1: 11 Temperature Bins	-1.2	-0.4	7.0			5.4	5.3	31.9
	(0.3)	(0.2)	(2.2)			(2.3)	(2.3)	(14.0)
2: Heating and Cooling Degree Days (Base of 65° F)				-2.1	3.8	1.8	1.7	10.2
				(0.5)	(0.8)	(1.1)	(1.1)	(6.6)

Notes: The estimates are from fixed-effect regressions based on a sample of 1,715 state-year observations. Each model includes state fixed-effects and census division-by-year effects. The dependent variable is the log of the total residential energy consumption in a state-year. Control variables include quadratics in population, state GDP, and their interactions, as well as a set of 11 indicator variables capturing the full distribution of annual precipitations. In the row 1. specification, temperature is modeled with the 11 temperature bin variables, while row 2 models temperature with the heating and cooling degree days (both calculated with a base of 65° F) and their squares. Standard errors are clustered at the state level. See the text for further details.

TABLE 7: ALTERNATIVE ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL RESIDENTIAL ENERGY CONSUMPTION,

	Hadley 3 A1FI, Error-Corrected		Hadley 3 A1FI		CCSM 3 A2	
	Bins	CDD and HDD (Base 65° F)	Bins	CDD and HDD (Base 65° F)	Bins	CDD and HDD (Base 65° F)
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
A. Baseline Estimates (10F-100F)	**5.3**	**1.7**	**5.7**	**3.6**	**2.4**	**1.7**
	(2 3)	(1.1)	(2.1)	(1.0)	(1.1)	(0.7)
B. Alternative Specifications						
1. Temperature range 10F-90F	**1.7**	---	**3.1**	---	**1.5**	---
	(1 1)		(1 0)		(0.7)	
2. Year Effects Only	**2.6**	**1.4**	**3.4**	**3.3**	**1.3**	**1.0**
	(2.4)	(1 0)	(2 4)	(1.2)	(1 0)	(0 6)
3. Controls for Daily Minimum and Maximum Temperature Separately	**0.9**	---	**2.8**	---	---	---
	(1.1)		(1 2)			
4 Add Previous Year's Temperature Variables	**5.2**	**1.6**	**5.6**	**3.5**	**2.5**	**1.6**
	(2.8)	(1.0)	(2 5)	(0 9)	(1.3)	(0.7)
5. Add Variable for Number of "Heatwaves"	**2.6**	**2.5**	**5.7**	**3.9**	**2.4**	**1.4**
	(2 4)	(1.1)	(2.0)	(1.0)	(1.0)	(0.7)
C. Impacts of Estimating the Response Function on Subsets of the Data						
1 Sample Restricted to Post-1980 Data Only	**2.0**	**-0.5**	**3.2**	**1.8**	**0.8**	**-0.1**
	(1 6)	(0.5)	(1.5)	(0.5)	(0 7)	(0 5)
2. Sample Restricted to States Above the National Median in the Number of Days Exceeding 80° F	**2.3**	**-0.2**	**3.2**	**1.8**	**1.0**	**0.4**
	(2.7)	(1.3)	(2.3)	(1.1)	(1 2)	(0 9)

Notes: The estimates are from fixed-effect regressions based on a sample of 1,715 state-year observations. Each model includes state fixed-effects and census division-by-year effects. The dependent variable is the log of the total residential energy consumption in a state-year. Control variables include quadratics in population, state GDP, and their interactions, as well as a set of 11 indicator variables capturing the full distribution of annual precipitations. The specification of the temperature bins and heating and cooling degree-days models is described in the notes to Table 5. See also the notes to Table 4 for a description of the alternative specifications (Panel B) and subsets of the data (Panel C). Specification B.1 is based on 10 temperature bins instead of 11. The state-level measure of heatwaves used in model B.5 is the weighted average of the number of heatwaves across all counties in a state. Standard errors are clustered at the state level. See the text for further details.

TABLE 8: ESTIMATES OF THE PRESENT DISCOUNTED VALUE OF THE HEALTH RELATED WELFARE COSTS OF CLIMATE CHANGE BY 30 YEAR PERIODS

	Change in		Present Discounted Value of Welfare Loss ($2006 Bil.)	
	Life-Years	Energy Consumption (Quads)	Current Prices	Assume Standard Annual Increases in Energy Prices and Value of a Statistical Life Year
	(1a)	(1b)	(2a)	(2b)
Hadley 3 A1FI, Error-Corrected				
2010-2039	-3,391,784	6.9	$181.50	$413.2
	(5,330,513)	(6.6)	($293.6)	($595.9)
2040-2069	-16,502,506	42.5	$404.6	$2,300.0
	(12,978,907)	(22.6)	($301.3)	($1,558.2)
2070-2099	-27,785,848	107.2	$306.4	$6,096.9
	(21,605,718)	(49.6)	($219.3)	($3,376.7)
Total	-47,680,138	156.6	$892.5	$8,810.1
	(39,915,138)	(78.8)	($791.4)	($5,530.8)
Hadley 3 A1FI (Actual)				
Total	-122,492,821	319.3	$3,233.5	$19,120.0
	(55,921,061)	(99.5)	($1,291.8)	($7,507.4)
CCSM 3 A2				
Total	-63,049,751	136.4	$1,702.9	$8,921.1
	(33,549,105)	(56.8)	($791.4)	($4,293.8)

Notes: Column (1a) reports the predicted change in life-years over different periods. The total rows refer to the years 2010-2099. Column (1b) reports the predicted change in energy consumption in quads. The column (2a) calculations assume that the value of a statistical life year is $100,000 and that the cost of a quad of energy is $7.6 billion. The column (2b) calculations assume that energy prices increase by 5% real annually Additionally, they assume that real per capita income grows by 2% per year and following Costa and Kahn (2004) that the elasticity of the value of a statistical life year with respect to income is 1.6. All present value calculations use a 3% discount rate. Standard errors are reported in parentheses. See the text for further details.